Evaluating Innovation Investment Outcomes of Government Venture Funding: A Longitudinal, Multi-Level, Multi-Source Analysis of Small Firms in the U.S.

by

Ana Scedrova

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Abstract

The study examines the role of government venture funding in facilitating entrepreneurship and innovation. In particular, the study integrates financial and behavioural perspectives in a unified framework to analyse the determinants and outcomes of innovation investments designed to help small firms commercialise their research and development activities. On the one hand, it draws upon real options reasoning theory to understand the effects of various resource allocation strategies on investment yield and firm performance. On the other hand, it uses signalling theory and the attention-based view to examine which individual-, project- and firm-level characteristics affect early- and late-stage funding allocation decisions, and whether these signals are also accurate predictors of investment yield and firm performance.

To investigate government investment patterns, 367 projects from 275 firms that participated in the Small Business Innovation Research (SBIR) programme administered by the National Health Institute in the U.S. were analysed over a seven-year period from 2006 to 2012 using a combination of statistical and econometric techniques.

First, the study finds that the formal real options reasoning (ROR) structure evident in the composition and execution of the government venture funding programme is only intuitively underpinned by the real options logic of decision-making. The results reveal that high initial funding commitment and continuation of government venture funding have a diminishing effect on return on investment, whereas consistent matching of funding decisions in line with ROR allows to extract value from staged investments. Second, drawing on signalling theory and attention-based view helps uncover discrepancies between prescribed and actual investment behaviour. Third, to benefit from options-like investments, firms require different combinations of skills and capabilities depending on their experience and the target performance outcome.

In sum, the study adds to the empirical body of literature analysing the tension between economic logic of efficient resource allocation and behavioural and cognitive effects on rational sense-making. The analysis delineates boundary conditions of real options reasoning in the context of government venture funding, which provides important implications for strategic management theory and research policy.

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Chapter 1 - Introduction

1.1 Introduction

New project development is at the heart of innovation and entrepreneurship but is costly. Nascent entrepreneurial ventures require financial resources to convert ideas into products. Since private funds are often limited, entrepreneurs seek capital from other sources and approach external finance providers. Start-up firms lack substantial tangible assets, have no track record of performance, promise no immediate returns and have uncertain prospects, which makes them dubious bets in the eyes of bankers and debt providers (Gompers and Lerner 2000). This is where venture capitalists come into play to fill the void in small firm financing (Jeng and Wells 2000). Venture capital (VC) firms disproportionately fund nascent ventures in high-tech industries and have the extensive expertise necessary to carry out the rigorous selection and evaluation processes to screen and filter candidates for potential funding. However, although venture capital firms are less susceptible to costs associated with information asymmetry than other external funding providers, they still favour lower-risk later stage candidates (Amit et al. 1998) and have the funds to support only a small fraction of new ventures (Lerner 2002). As a result, there exists a funding gap at early stages of the small firm development.

The extant literature holds a uniform view that well-developed capital systems stimulate technological innovation, which subsequently leads to productivity growth and economic development (King and Levine 1993a; 1993b). In particular, the role of capital markets is pronounced in spurring innovation-induced 'creative destruction' in the economy (Schumpeter 1942) by supporting small firms in high-tech industries (Brown et al. 2009; Hsu et al. 2014). To compensate for the failure of financial markets to provide adequate capital to high-risk early-stage ventures, governments intervene with the initiation of public funding programmes. Numerous studies have been dedicated to evaluating the role of public subsidies in fostering innovation and entrepreneurship, in particular in comparison to private venture capital. For the most part, the extant literature shares the view that venture capital, both private and public, has a positive impact on firm growth, employment creation, innovative activity and country-level economic growth. However, much less is understood about what effects different resource allocation strategies have on performance outcomes of investors and investees. Additionally, little is known about the behavioural aspects at play in the seemingly rational process of sequential investments followed by decision-makers. These questions are particularly important in relation to government venture capital, which is frequently being criticised for its questionable ability to allocate taxpayers' money appropriately.

This chapter sets the scene for the entire study by outlining the research motivation, theoretical and empirical gaps. The chapter ends with a synopsis of the thesis.

1.2 Rationale for Conducting the Research Project

Research Motivation

Why is Financing Small and Medium Enterprises Important?

It is well established that technological change is at the heart of economic growth (Solow 1957; Romer 1990). Therefore, to achieve economic growth, governments need to establish a robust innovation system (Guan and Chen 2012).

There is a general consensus that encouragement of market competition through entrepreneurship is a way to add value to a society (Birley 1986). A significant amount of effort continues to be dedicated to understanding in what ways entrepreneurship creates value in a society. A number of studies found statistical evidence that new venture creation has a positive effect on innovation and job creation, which subsequently influences regional development, state welfare and economic growth (Acs and Armington 2004; Acs and Audretsch 1988; Acs and Varga 2005; Wennekers and Thurik 1999; Stel et al. 2005).

More specifically, recent evidence from a novel multi-country dataset demonstrated a positive effect of the size of the small and medium enterprise (SME) sector on economic growth, expressed by the GDP per capita (Beck et al. 2005). However, Beck and colleagues (2005) found no causal link, implying that the growing SME sector is not a direct underlying cause, but instead a characteristic of economic wealth. While the direct effect of SMEs on economic growth is disputable, strong evidence exists of a significant contribution of SMEs to employment creation (Birley 1986). For example, a recent cross-country study by Ayyagari et al. (2007) showed that the SMEs in the manufacturing sector make up at least 50% of the total country employment.

There is a longstanding literature on the role of small firms in innovation. A considerable amount of scholarly work has presented evidence that despite their low level of R&D spend, small and medium size enterprises contribute a significant proportion of total R&D knowledge produced (Audretsch 2003). As Acs and Audretsch (1988) estimated, the share of innovations from small firms on average constitutes 40% and those innovations are of comparable quality and importance to the ones from larger firms. Furthermore, Akcigit and Kerr (2015) documented that the rate of the main technological inventions and patent citations is higher in small firms, which indicates that small firms yield greater spillovers to the economy. Overall, it has been recognised that projects undertaken by the SMEs contribute around 20% to the private sector economy (Turner et al. 2009).

In spite of a large share of the SMEs in total employment and innovation across the globe, their contribution to the economic growth is much smaller, which is in part attributable to a number of constraints, in particular, access to finance, that prohibits them from growing as much as their larger counterparts. On a global scale, less than 2% of firms with 10 or more employees grow sufficiently in terms of employment and revenue to evolve into 'gazelles'—small firms with an annual growth of at least 20% (OECD 2015a). Despite representing a minor part of the total SME sector, 'gazelles' are a driving force behind economic development, in particular in terms of employment and wealth creation. For instance, OECD data (2015a) showed that in 2012, 36,000 high-growth ventures in the U.S. employed over 8 million people. The importance of 'gazelles' for economic development has been acknowledged by public policy makers around the world, and effort has been made towards designing appropriate mechanisms to support the high pace of growth among small firms (Grilli and Murtinu 2011).

To understand the reasons behind differences in growth rates of new ventures, much interest has been directed at exploring which institutional arrangements stimulate or inhibit entrepreneurial risk-taking in pursuing opportunities for potential value creation (e.g. Busenitz et al. 2000). Competitive business environments that have regulatory arrangements in place, such as low cost of incorporation, access to finance, favourable labour laws, efficient credit information sharing and protection of intellectual property, facilitate new firm entry and SME sector growth (Klapper et al. 2006; Beck and Demirguc-Kunt 2006; Ayyagari et al. 2007). Beck and Demirguc-Kunt (2006) emphasised that developing favourable business environments for new firm entry is even more important for economic growth than facilitating the growth of the SME sector, which is often characterised by a large number of small but stagnating firms.

Klapper et al. (2006) in their study on entry barriers to entrepreneurship found that improved access to start-up capital, a feature of more financially developed markets, is associated with higher new firm creation. Similarly, a literature review by Gilbert and colleagues (2006) revealed that human and financial resources are vital for the growth of new ventures. A recent survey of extant literature on SMEs by Beck and Demircut-Kunt (2006) concluded that access to capital is a critical growth constraint for SMEs and that financing mechanisms independently or in conjunction with institutional arrangements can mitigate problems associated with obtaining start-up finance. Furthermore, Zerbinati and colleagues (2012) provided evidence that early growth of research-based spin-offs is mainly attributed to the initial capital investment in those ventures.

As Atanassov (2016) expressed it, the positive effect of well-developed capital markets on stimulation of R&D is twofold: relaxation of financial constraints makes funds more easily accessible for development of innovative projects and creates stimuli to engage in more risky and novel endeavours, particularly for small firms (Brown et al. 2013; Brown et al. 2012). Consequently, reduction of financing constraints is an important channel that facilitates technological innovation and, consequently, economic growth (Bekaert et al. 2005; Brown et al. 2012).

Research Problem

Risks Associated with Limited Access to Finance by the Small and Medium Entrerprises

Experimentation is an integral part of R&D and is a core ingredient for innovation. Early stages of R&D have been described as the 'fuzzy front end' due to the high levels of associated uncertainty (Khurana and Rosenthal 1997; Khurana and Rosenthal 1998; Koen et al. 2001). A number of studies have shown that early stage activities are crucial for innovation success (e.g. Markham 2013; Kock et al. 2015). Furthermore, evidence exists that being highly effective at idea conversion[1] is more important to financial and innovation success than being highly skilled at generating ideas (Booz&Co 2012).

Experimentation[2] is also an expensive process that requires time and financial commitment. To raise capital an entrepreneur has to approach external funders. Financing SMEs is problematic due to asymmetric information flows, which cause adverse selection[3] problems (Bouvard 2012), with an entrepreneur holding private information to which an investor has only limited access. Further to that, R&D projects conducted by the SMEs are even more susceptible to financial constraints because of inherent uncertainties surrounding them.

Conventional capital providers such as banks are reluctant to provide finance to small firms with uncertain prospects as there exist information gaps between entrepreneurs and investors (Lerner 2002). Venture capital firms, however, specialise in screening and monitoring risky ventures in high-tech industries, which gives them a comparative advantage in dealing with information asymmetries (Brander et al. 2014). Although private venture capitalists disproportionately fund start-ups, they still favour the less risky ones (Amit et al. 1998), which restricts access of early stage ventures to capital.

Also, the venture capital industry is only accountable for a minor fraction of the total investment activity. Global data show that in the majority of countries, venture capital represents a very small proportion of GDP averaging 0.05%, with the U.S. being the notable exception, representing 0.28% of GDP and 80% of the total OECD venture capital investment in 2014 (OECD 2015a). Nonetheless, on average, venture capital provides finance to less than 0.1% of firms and even less in the times of the financial crisis, when the average size of investment surges (OECD 2015a).

[1] Conversion stage refers to the phase in the process where ideas in the pipeline are screened and selected for full-scale product development (Booz&Co 2012).
[2] Experimentation stage refers to the early phase of project research and development activities, which involves collection of information to minimise the associated uncertainty and to inform the future trajectory of actions, including investment decisions (Bouvard 2012).
[3] Adverse selection arises as a result of funders' limited ability to differentiate between low-quality and high-quality borrowers and leads to the erroneous allocation of funds to less profitable or unprofitable ventures.

Given the limited availability of private venture capital for small early stage firms, the screening procedure is critical yet problematic. A number of studies emphasised the tremendous complexity of ex-ante evaluations of the prospects of early stage innovative projects undertaken by the nascent ventures, and even well-established VC firms struggle with this task (Kerr et al. 2014). Evidence supports the notion that the adverse selection problem that arises when firms cannot reliably convey their abilities for the future potential to investors, results in substantial social losses, as foregone investment opportunities reduce the stream of prospective public value[4] creation (Myers and Majluf 1984).

SMEs' constrained access to funds, magnified by the 'liability of newness', causes underinvestment in R&D due to the danger of knowledge appropriability. R&D is considered as one of the most economically valuable knowledge sources (Audretsch 2003). The impact of R&D activities of small firms is significant at two levels. The direct impact is attributable to small firms that translate internally produced novel R&D knowledge into technological innovations. The indirect contribution of R&D of small firms to economic value creation takes the form of knowledge spillovers. That is, the internally generated knowledge shifts to the public domain and becomes available for open use. However, while R&D knowledge spillovers are critical for the economy, small firms are concerned about the issues of knowledge appropriability. One of the primary underlying rationales behind new venture creation is the intention of researchers to appropriate the economic value of their knowledge through organised innovation activity. Since knowledge cannot be kept secret, other economic agents will 'freeride', implying that the returns from the investment in its production will not be fully appropriated by its original source (Hall and Lerner 2010). Therefore, innovation efforts yield higher social returns than private returns (Griliches 1992; Beck et al. 2016). As a result, the unprohibited use of knowledge by the public is perceived as a threat by the original knowledge producers, in that case, small firms, which results in underinvestment in R&D—the idea originally expressed in the seminal work of Nelson (1959). Underinvestment in R&D can take the form of the project scale down or complete discontinuation (Feldman and Kelley 2006), thereby impeding economic development. Yet, conservative estimates suggest that the optimal R&D investment is between two and four times higher than the actual investment (Jones and Williams 1998).

From the above discussion, two primary problems become apparent that prevent entrepreneurs from pursuing potentially fruitful opportunities. First, external funding providers are unable to accurately assess future potential of new ventures due to the volatility of returns from innovation projects and information asymmetries. As a result, there is a lack of available finance to SMEs, which significantly inhibits their potential for growth (Gilbert et al., 2006). Second, financial

[4] Public value reflects direct and indirect economic outcomes that can be appropriated by the society.

constraints magnify concerns of small firms about knowledge appropriability, leading to underinvestment in R&D and slower economic growth.

To reduce the financing gap and capital constraints caused by market imperfections and to stimulate innovation in the SME sector, governments from around the world intervene with the provision of public financing programmes for the private sector (Brander et al. 2014). There are two primary mechanisms that policy makers utilise to mitigate inefficiencies of capital markets in support of entrepreneurship. One is indirect involvement through R&D tax initiatives, intellectual property protection and reinforcement of various co-operation systems; another is direct investments in R&D (Hall and Lerner 2010). Evidence exists that public capital sources provide over 60% more financial support for SMEs than private venture capital, with particular emphasis to ventures in early stages of development (Audretsch 2003). Moreover, public funding minimises the cost of socially valuable R&D to a level at which firms have an incentive to undertake the project (Aerts and Schmidt 2008).

Practical Relevance

What is the Magnitude of Governmental Support of Small and Medium Enterprises?

Small Business Innovation Research (SBIR) programme launched in 1982 in the U.S. was the first of its kind. Its initiation was intended to fuel technological growth in response to the productivity slowdown in the U.S. Over the years, 11 Federal agencies administering the programme have awarded over 100,000 grants to small firms in technological sectors, some of which have grown into multi-million and multi-billion corporations such as Qualcomm in the semiconductor industry, Symantec and iRobot in the advanced technology industries and Genentech in the biotech industry, just to name a few. By recognising the importance of knowledge-based nature of the SMEs, the SBIR programme took the lead in promoting knowledge commercialisation of the SME sector in a number of critical industries, including biotechnology (Audretsch 2003). The success of the SBIR programme has inspired similar initiatives around the world, and now the governments of most major economies have innovation programmes in place, including Russia's Skolkovo Foundation, Australia's National Innovation and Science Agenda, India's National Innovation Foundation, Japan's Small and Medium Enterprise Agency, and China's Innofund.

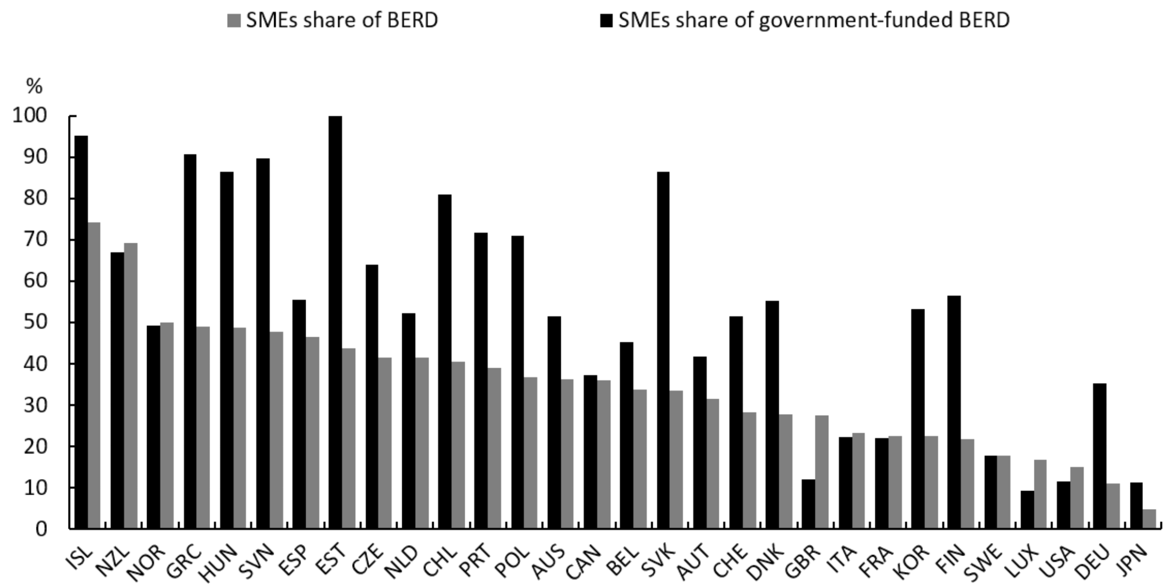
In the same vein, most European governments have launched initiatives to stimulate innovation among the SMEs[5] and the EU has taken a lead by introducing Eurostars Programme. Under the Seventh Framework Programme (FP7), Eurostars had a public budget of €400 million for 2007-2013, which has been increased to €1.14 billion for 2014-2020 under the Horizon 2020 Framework to

[5] A full list of European national innovation programmes is presented in Appendix 1.

meet the growing demand by the European SME applicants. Eurostars is 75% backed by national funds and 25% by EU funds, and although the projects are only up to 60% funded by the scheme, a sizeable budget of €1.5 billion has been set aside during 13 years of operation.

According to the OECD report on Science, Technology and Industry (2015b), the level of government investment varies country by country. Three investment patterns become apparent from Figure 1-1. Government investment in R&D of small firms in countries like New Zealand, Norway, Canada, Italy, France and Sweden, is proportionate to the share of R&D of small firms in the gross domestic R&D expenditure. On the other hand, in countries like Iceland, Greece, Slovenia, Chile, Portugal, Poland and Slovakia government funding goes almost exclusively to SMEs. Finally, U.K., Luxembourg and U.S. have a shortage of government support for R&D activities of small firms.

Figure 1-1: 2013 share of SMEs expenditure on R&D as percentage of gross domestic expenditure on R&D

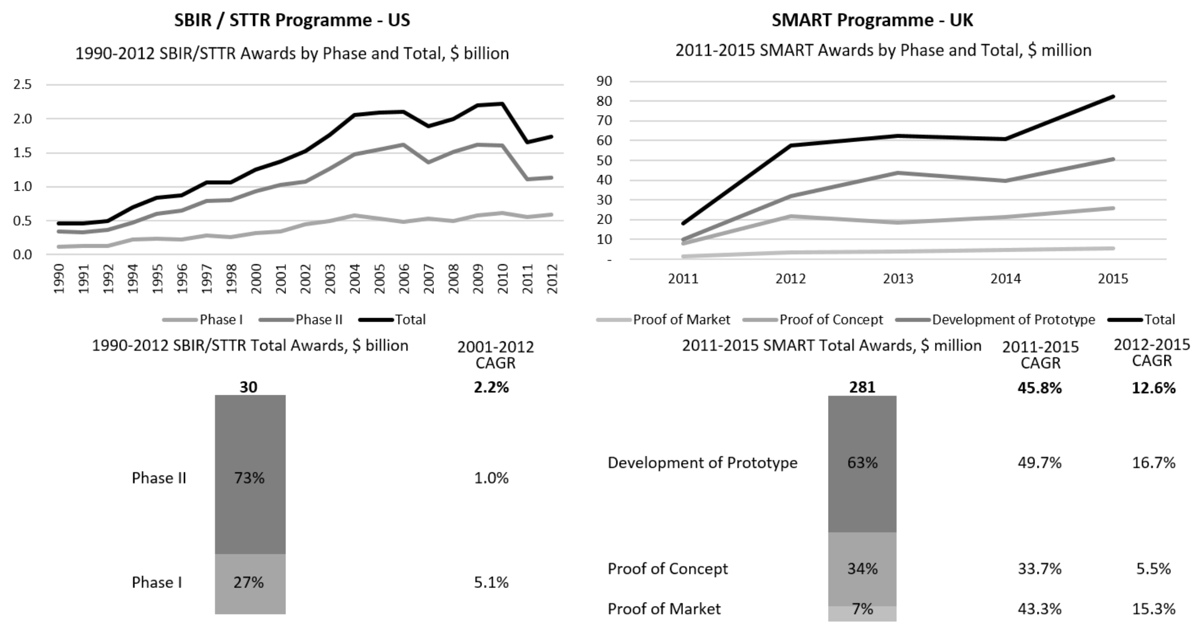


Notes: Business enterprise expenditure on R&D (BERD) - gross expenditures on R&D performed by all for-profit public and private firms, organisations and institutions.
Government-funded business R&D (BERD) - is the component of R&D attributed to direct government funding such as grants and payments for R&D contracts for procurement, but <u>not</u> R&D tax incentives, repayable loans or equity investments.

Source: OECD Report on Science, Technology and Industry Scoreboard 2015

However, a closer look at the government contribution of “underspending” countries in absolute terms, changes the picture dramatically. Figure 1-2 compares government funding programmes in two major economies: U.S. and U.K. Although the programmes have been in operation for a different number of years, with the SMART programme launched 30 years after SBIR, the trend is apparent of both schemes incrementally increasing budgets on an annual basis except in recession times. And although for both the U.S. and the U.K. the annual spend on programmes is less than a 10th of 1% of their respective GDPs, over the years the amount spent on the programmes has accumulated to a grand total. Over 22 years since 1990, the U.S. government has spent $30 billion on the SBIR initiative. Although on average the annual budget of the U.K.'s SMART programme is only 5% of its U.S.-based counterpart, in 4 years of running the programme, the U.K. so far has spent $281 million. Moreover, cross-country data from a study by Brander and colleagues (2014) demonstrated that government VC around the world on average dedicates $4 billion per year to small private ventures. These data confirm that the governments direct significant sums of public money in support of innovative SMEs.

Figure 1-2: The magnitude of government spend on SMEs: U.S. versus U.K.



Source: Author's analysis of data from SBIR and SMART

Summary of the Main Issues for the Current Project

SMEs significantly contribute to employment and innovation creation, but their role in fostering the economic growth is less prominent. In particular, limited access to finance constraints entry, high-paced growth and innovative activities of small firms. Financing constraints for SMEs exist for two primary reasons: (i) conventional capital providers are unable to resolve uncertainty due to information gaps; (ii) venture capital funds, although targeting start-ups, are more inclined to finance less risky candidates and have insufficient funds to take forward all high-potential ventures.

Imperfections of capital markets result in substantial social losses and are manifested in two major problems. First, limited access to finance by the SMEs leads to underinvestment in R&D. Second, identification of high-potential ventures through common due diligence, screening and evaluation procedures is difficult. To address market imperfections, governments of major economies initiate high-budget publicly-funded financing programmes to support entrepreneurship and innovation.

1.3 Brief Overview of the Research Field & Research Gaps

Literature on Financing of Innovation and Entrepreneurship

A large number of studies on external funding of innovation and entrepreneurship are concentrated on the role of the venture capital industry (Hall and Lerner 2010; Da Rin et al. 2013). As a result of their disproportionate support of high-risk but high-potential firms with no immediate returns (Puri and Zarutskie 2012), venture capital has become an important international channel for stimulating and managing the flow of funds and novel ideas (Patricof 1989). A number of studies have investigated the role of VC in broader terms and provided compelling evidence that VC-backed firms drive the development of high-tech sectors and contribute to innovative activity, employment creation and economic growth at the country-level.

Kortum and Learner (2000) examined the relationship between venture capital and innovation, and found that venture capital is associated with a substantial increase in patenting and quality of patents, as measured by forward citations. The authors demonstrated that VC-financed ventures are more innovative than non-VC-financed firms and generated 8% of industrial innovations in the United States in the decade ending in 1992 (Kortum and Lerner 2000). Likewise, the econometric analysis of Bertoni et al. (2011) showed strong support for the view that venture capital has a positive impact on the growth of new technology-based firms. Hellmann and Puri (1998) provided evidence that venture capital is crucial for innovative start-up companies as it positively affects their ability to introduce new products faster to the market.

To understand the role of venture capital in fostering entrepreneurship, a recent study by Puri and Zarutskie (2012) compared differences of VC-backed and non-VC-backed firms using data from the United States over 25 years. Their evidence shows that although VC-financed firms make up a negligible portion of the total newly created firms—0.11% for the period 1981 to 2005—their contribution to the employment is more significant, accounting for 5-7% during 2001-2005 (Puri and Zarutskie 2012). Additionally, VC-backed firms in the sample outperformed non-VC-backed firms in terms of sales and employment growth, higher IPO and acquisition rates and lower failure rates. Further, the results of Puri and Zarutskie (2012) showed that 40% of VC-backed firms fail, 34% are acquired and 16% go public, in comparison to 79% of non-VC-backed firms that fail and just over 1% that get acquired and go public. As a consequence, VC funds persistently earn higher average returns in comparison to other capital funds (Kaplan and Schoar 2005).

Enhanced performance of VC-backed firms is attributed to a number of factors. First, VCs provide funds to the ventures that have withstood rigorous selection criteria and those financial resources give entrepreneurs a chance to develop the venture into a high-growth profitable business

(Sahlman 1990). Second, venture capitalists provide value-added services and access to non-financial resources to nascent firms (Hellmann and Puri 2002). In particular, monitoring through staged investments is critical in mitigating agency problems (Gompers 1995). Finally, VC-backing has a certification effect in the market and alleviates the 'liability of newness' problem experienced by young firms (Hsu 2006). Taken together, these findings indicate the important contribution of VC financing in fostering innovation and entrepreneurship.

Governments of many industrialised economies around the world have started to appreciate the impact of SMEs on economic growth and the role of venture capital in developing entrepreneurial enterprises, and have intervened in the venture capital market with own programmes and initiatives designed to fund start-up firms (Jeng and Wells 2000; Brander et al. 2014).

Extensive efforts have been made to evaluate the role of government programmes in enhancing the economic value of entrepreneurial endeavours. Different questions were addressed from different analytical perspectives, concerning the effect of public funding programmes for R&D on: (i) input additionality, in particular with respect to the crowding out effect; (ii) output additionality, predominantly with a focus on the long-term outcomes; and, more recently (iii) behavioural additionality[6]. The findings of extant scholarly work are disparate with regards to the impact of governmental capital backing programmes. While some studies found evidence of a positive effect of government financing programmes on growth and performance of awardees (Lerner 1999), recent studies showed that the government VC-backed firms display significant reductions in productivity compared to their non-VC-backed peers (Alperovych et al. 2015).

Analysing the data on the SBIR initiative, a number of studies provided findings that government funded programmes can have a positive impact on firm performance (Lerner 1999). The results of Audretsch (2003) demonstrated that the SBIR programme is associated with a positive private and social rate of return. The findings of Elston and Audretsch (2010) suggested that SBIR grants reduce liquidity problems of less wealthy entrepreneurs as well as stimulate opportunity-seeking behaviour among risk-averse entrepreneurs. More recently, Howell (2015) documented an important role of government subsidies in relaxing financial constraints of small early-stage firms.

In addition to the direct positive impact of such programmes as SBIR on commercial performance of small firms, Cooper (2003) summarised their latent advantages as follows: (i) stimulation of entrepreneurial risk-taking behaviour of small firms with regards to novelty and scope of innovation activities; (ii) development of scientific human capital; (iii) certification of financial and operational legitimacy of awardees through the halo effect; (iv) reduced threat of knowledge

[6] The concepts of input, output and behavioural additionality are discussed in greater detail in the subsequent chapter dedicated to reviewing the extant literature.

appropriation as the government funding programmes do not take equity stake in nor claim IP rights for innovation projects; (v) support for projects in a wider range of research and geographical areas.

On the other hand, critics noted that such programmes can bear substantial costs to the taxpayers when poorly designed and implemented (O'Shea and Stevens 1998). Leleux and Surlemont (2003) criticised public VC for its propensity to misallocate funds, which may be a result of the paucity of government officials' suitable expertise for screening entrepreneurial ventures and non-performance-linked incentives structure. Additionally, concerns were expressed that public funds subsidise the wages of scientific human capital but have a significantly smaller impact on the level of inventive activity (Goolsbee 1998; David and Hall 2000).

Overall, the evidence on the effects of government funds to spur innovation and entrepreneurship remains equivocal. More importantly, sceptics cast doubts on the governments' ability to replicate the functions of the private venture capital, due to issues related to political and bureaucratic processes leading to inefficient resource allocations and rent-seeking behaviour (Lerner 2002).

Theory of R&D Investments

It is well established that R&D projects with high potential can enhance firm-level and country-level economic performance and competitive advantage (Lewis et al. 2002). However, innovation projects require substantial capital endowments, even though their chances of success remain low irrespective of the amount of support they receive (Klingebiel and Rammer 2014). This makes resource allocation a challenging task because decisions have to be taken before a portion of endogenous uncertainty is resolved.

Three characteristics are inherent in the majority of investment decisions: (i) they incur unrecoverable sunk costs, (ii) information asymmetry adds to the enduring economic uncertainty and, (iii) decision on whether to invest is equally important as when to invest (Dixit 1992). For investments that encompass all these characteristics, the value of waiting has a positive effect as uncertainty regarding future prospects can be resolved with time through the arrival of new information. Such approach towards investments under conditions of uncertainty has been coined *"a theory of optimal inertia"* or *"a benevolent tyranny of the status quo"* (Dixit 1992 p.109). The value created through waiting is at the core of real options financial models, under which potential yield from investments is assessed through flexible sequential decision-making practices. Analogous to financial options, real options in strategic management are created through splitting a large financial commitment into several smaller investments and distributing them over time (Miller and Waller 2003). Such staged investment tactic enables flexible and timely responses of decision-makers to unfolding possibilities, minimising downside risks and maximising upside potential benefits.

R&D projects have a number of prominent features that make them distinct types of investments. First, research has highlighted that R&D investments are characterised as particularly irreversible capital (Dixit and Pindyck 1994). R&D costs predominantly cover the salaries of scientific personnel as well as equipment and materials necessary to conduct the project, and cannot be recovered in the case of unsuccessful outcome (Toole and Czarnitzki 2009; Czarnitzki and Toole 2011; Czarnitzki and Toole 2013). Second, R&D investments have a high uncertainty component and evaluation of payoffs from the possible outcomes goes above and beyond simple risk assessment exercises (Kerr and Nanda 2014). Third, resolution of R&D uncertainty is in part dependent upon tacit knowledge engrained in human capital, making an estimation of projects' future potential difficult as there is a threat of losing uncodified knowledge if project members leave the team (Hall and Lerner 2010). Fourth, project assessment task may be further complicated by the level of funders' expertise in dealing with risky endeavours, incentives, decision-making heuristics and interpretative practices, which may lead to under- or over-involvement of funders in shaping the direction of R&D activities (Kerr et al. 2014). Fifth, project owners inevitably have more information on the R&D project than project funders, thereby enhancing information asymmetry. Finally, the way the investment process is structured has a significant impact on the type and trajectory of innovation (Kerr and Nanda 2014).

It is widely known that innovation projects are associated with high failure rates, which increases the likelihood of considerable financial loss (Schmidt et al. 2009). Progression of the project through the stages of development clarifies uncertainties by generating new information, but also entails rising resource commitments (Cooper and Kleinschmidt 1986). Therefore, early elimination of failures becomes an imperative to avoid significant investment loss and can be achieved by discontinuing projects as a result of increased and disciplined monitoring and review practices (Schmidt et al. 2009). The notion of early pruning of the project portfolio becomes even more critical taking into account that financial markets react more favourably to new product development failure in early stages than in late stages of the innovation process (Urbig et al. 2013). Therefore, the mechanisms that stimulate experimentation are vital for maintaining vibrant innovation systems and, subsequently, the entrepreneurial economy (Dosi and Nelson 2010).

The real options framework is one such mechanism that supports the notion of experimentation (Kerr et al. 2014; Nanda and Rhodes-Kropf 2016). The unique characteristics of R&D investments, which encompass irreversibility, uncertainty, flexibility and information revelation, enable to view such investments as options (Krychowski and Quelin 2010). Therefore, real options lens is naturally suited to extracting value from the staged innovation projects (Dixit and Pindyck 1994; Hall and Lerner 2010; Krychowski and Quelin 2010) as learning about the prospects of a new technology is less costly in early stages of the investment process (Kerr et al. 2014). The inexpensive experimentation channel is especially critical for the nascent financially constrained ventures since the sooner resolution of project uncertainty, which is greatest in the early phases, shapes the trajectory of future aggregate innovation activity (Ewens et al. 2015). The primary advantage of real options is confined to its ability to explicitly comprehend the evolving nature of investment projects and to foster a more flexible approach to resource allocations (Krychowski and Quelin 2010). As a consequence, venture capital firms often follow the real options approach to allocating resources to innovation projects (Hurry et al. 1992; Guler 2007b; Guler 2007a).

Theoretical Gaps

Although the extant literature on real options theory is conceptually well developed, there remain a number of under-researched areas that constrain the full comprehension of the conceptual underpinnings of the theory. Specifically, the most widely discussed shortcomings of the real options theory pertain to three primary issues: (i) implementation of real options approach by the organisations may not be in close agreement with the theory; (ii) behavioural and cognitive aspects may introduce bias to the real options decision-making process and, (iii) the approach may not be applicable to all strategic investments (Krychowski and Quelin 2010).

Broadly speaking, the questions remain on *whether* and *how* organisations can effectively implement the real options to capture the value offered by such approach (McGrath et al. 2004). Identified theoretical gaps are articulated in detail subsequently.

Agreement of Real Options Theory with Practice

As Krychowski and Quélin (2010) observed, the interpretative and decision-making frameworks of real options theory evolved separately from each other, resulting in somewhat disparate conceptual underpinnings. On the one hand, the interpretative strand of research is built upon the belief that organisations implicitly align their strategic thinking with the real options approach. On the other hand, the decision-making strand of research argues that the real options approach creates value only if organisations implement it systematically rather than casually.

The extant literature is abundant in studies on the rhetorical formalisation of real options theory; yet, little empirical evidence exists on the extent to which firms implicitly or explicitly follow the prescriptions of the real options approach in the organisational settings (Reuer and Tong 2007). It was suggested that to advance and clarify propositions of real options theory, future research should focus on understanding organisational practices in implementing the real options approach (McGrath and Nerkar 2004).

Therefore, real options theory could be further enriched by examining the interplay of its descriptive and normative tenets, which by itself is a challenging task (Krychowski and Quelin 2010). Currently, the evidence shows that organisational decision-makers often intuitively, albeit infrequently and only approximately, follow the real options reasoning (ROR) logic (e.g. Busby and Pitts 1997; Triantis 2005; Howell and Jaegle 1997). However, it is still unclear to what extent deviations from the prescriptions of the real options logic distort the process of value creation. Specifically, it is important to test whether the judgements of organisational decision-makers follow propositions of the theory (Howell and Jaegle 1997).

Overall, a better understanding of whether and to what extent the formal and disciplined implementation of the real options approach is associated with performance improvements is expected to inform organisational decision-making (Krychowski and Quelin 2010).

Reconciliation of Financial and Behavioural Aspects of Real Options Theory

One of the core strengths of real options theory relates to its ability to merge financial and behavioural perspectives. As such, not only it helps understand the budgeting principles, but also to capture the effects of decision-making practices on organisational performance in relation to a single option or a portfolio of options (Krychowski and Quelin 2010).

Organisational research integrating financial and behavioural theories remains scarce, and little progress has been made towards understanding decision-making processes underpinning innovation investment outcomes (McGrath and Nerkar 2004). It was expressed that empirical studies testing propositions of real options theory have started to emerge in the recent years in the strategic management literature (e.g. McGrath and Nerkar 2004; Hurry et al. 1992). Still, more research is needed to examine the correspondence of the theory with decision-making practices, accounting for heuristics and biases inherent in the process (Scherpereel 2008).

Resource Allocation Strategies under Real Options Theory

Existing literature offers little insight into the advantages provided by resource allocation strategies under ROR (Krychowski and Quelin 2010). One of the notable benefits of the real options lens is confined to its ability to explicitly investigate the heterogeneous effects of different resource allocation strategies on organisational performance. However, although conceptual aspects of resource allocation strategies have attracted some scholarly attention (e.g. Ding and Eliashberg 2002), despite its practical importance, little empirical research exists on the topic (Klingebiel and Rammer 2014), especially using the real options reasoning lens.

Applicability of Real Options Theory to Organisational Contexts

As was noted above, the academic debate on the boundary conditions of the real options reasoning called for more evidence on whether the actual investment behaviour is consistent with the theoretically predicted with regards to exercising options (Li and Chi 2013).

More precisely, it was argued that when the theory is tested in broad organisational settings, it provides little insight into the specific benefits of the approach (Krychowski and Quelin 2010). Instead, a number of prior studies acknowledged that understanding of real options theory can be further enhanced through studying investment portfolios in different empirical contexts. For instance, scholars have been encouraged to test real options theory in relation to R&D and technological projects of start-up or small firms funded by venture capital (Trigeorgis 2005).

The Role of Resources and Capabilities in Real Options Theory

Last, but not least, the potential interrelationships between real options and different categories of human capital and firm resources have been recognised in prior literature (Janney and Dess 2004). However, limited work exists that has explicitly investigated the impact of industry-level, firm-level and individual-level resources and capabilities on real options performance outcomes in a single conceptual framework (Chang 1995; Leiblein and Miller 2003; Lu and Beamish 2004; O'Brien et al. 2003). Evidence shows that the level and heterogeneity of resources and capabilities shapes the way firms react upon and manage options (Bowman and Hurry 1993). Hence, research analysing the impact of heterogeneous firm-specific factors on the processes underlying the options-based investment structure has been identified as a promising area for future studies (Li et al. 2007).

Empirical Gaps

In addition to theoretical gaps outlined earlier, a number of empirical gaps have been identified that relate to contextual settings as well as methodological and measurement issues.

Resource Allocation Strategies of Public Venture Capitalists

As was mentioned in the previous section, there was a call to test the principles of real options theory in different empirical settings. Specifically, review of the extant literature has identified that while sequential investments in the private venture capital industry have attracted some scholarly attention (Guler 2007a; Guler 2007b), to the best of knowledge, no such study was conducted on investment patterns of public venture capital.

In particular, there remains an opportunity for researchers to advance the knowledge of the impact of governmental subsidies for R&D by incorporating the structural aspects of resource allocation strategies into a coherent model (Klette et al. 2000).

It was also expressed that future research on the public venture capital programmes should integrate human capital characteristics of academic entrepreneurs to better comprehend the selection and evaluation processes (Toole and Czarnitzki 2007).

Multi-Stakeholder View of Venture Performance Outcomes

As Lerner (1999) noted, it is hard to evaluate the effectiveness of the government programmes as a function of firms' ability to maintain the rate of internal R&D spending by the awardees; instead, the long-term economic impact of awards has been recognised as a critical issue (Lerner 1999).

Assessment of the performance of funded projects is an important task in organisation and policy domains as it allows to estimate whether investments yield anticipated gains. There has been criticism that a large proportion of existing studies evaluate project performance from the process-oriented perspective (Zwikael and Smyrk 2012). However, this approach sheds a little light on the implications of funding decisions.

To address this issue, Zwikael and Smyrk (2012) proposed that project success should be assessed from the investment-oriented perspective in terms of its net worth. The authors developed a multi-stakeholder framework that explicitly evaluates project performance from the funder's, project owner's and project manager's perspectives in relation to target outcomes of each group. Under this view, the firm owning and managing the project becomes the funder's agent and is accountable for the realisation of target outcomes, which are different for both groups (Zwikael and Smyrk 2012).

Multi-Level Conceptual Model

There has been a call for more multi-level research efforts in the entrepreneurship domain (Hoskisson et al. 2011). Low and MacMillan (1988) pointed out that increased and continuing use of the multi-level approach to theory and methodology would improve the understanding of the entrepreneurship field. Traditionally, entrepreneurship studies have been conducted at the individual level of analysis. And, although entrepreneurship research has seen a rise of scholarly work incorporating firm-level analysis, more still needs to be done to advance the field (Hoskisson et al. 2011). In particular, multi-level research should attempt to address interactions of micro- and macro-level antecedents that lead to improved outcomes of entrepreneurship activity such as innovation, competitive advantage and firm performance (Hoskisson et al. 2011).

Research Policy Gaps

There is generally a wide consensus in academic and research policy domains on the appropriateness of government intervention to stimulate innovation activity in the SME sector. However, *"compared to the size of the programmes and the emphasis put on technology policy by politicians, the effort to evaluate in quantitative terms the economic benefits and costs of R&D subsidies has been rather modest"* (Klette et al. 2000).

It was noted that although studies on public venture capital programmes have gained momentum in the last decade, the evidence on the effects of government funds to subsidise R&D efforts of SMEs remains inconsistent. As a result, there was a call for more studies evaluating the effectiveness and limitations of such initiatives (Pavitt 1998; Bayona-Saez and Garcia-Marco 2010) as well as their impact on entrepreneurship and innovation (Cumming and Li 2013).

More precisely, there is still a limited understanding of how such initiatives should be structured to reap maximal benefits and to restrain politically and bureaucratically induced inefficiencies (Lerner 2002). Despite the prevailing belief that governmental programmes are associated with a number of advantages, more recent studies have called their efficiency into question, suggesting that they merit re-evaluation and perhaps a comprehensive reformation of an underlying structure (Alperovych et al. 2015).

1.4 Brief Overview of the Research Project

Research Objectives & Questions

Although there is a sizeable body of literature that has been dedicated to examining *whether* capital markets impact innovation and entrepreneurship, there has been much less focus on understanding *how* capital markets might influence technological innovation and growth of small firms. The focal interest of the current project is a specific type of external finance—direct governmental support for the innovation activities of the SME sector. Here, the assumption is made that by using a staged investment process of value creation and by selecting high-potential candidates, the government chooses to act as a public venture capitalist. More precisely, the present research study pursues three primary objectives.

The first objective is to investigate the financial decisions underpinning the resource allocation process of government venture funders. The aim is to understand which elements of the budgeting strategy are associated with enhancements in investors' and firms' performance. The first objective can be formulated as the following research question: *What effect do various funding allocation decisions have on long-term performance outcomes of investors and investees?*

The second objective is to understand the evaluation process and selection criteria that public capital investors follow to allocate funding to candidates. Additionally, attention is devoted to the behavioural aspects of the resource allocation process. That is, the intention is to grasp which characteristics of candidates receive higher weights among public capital investors. Furthermore, the interest lies in exploring whether the evaluation process is subject to decision-making bias or distortions and whether investors use heuristics to minimise information asymmetry associated with the assessment of innovation projects. The research question articulated by the second research objective can be expressed as: *Which firm-level, project-level and individual-level characteristics affect early- and late-stage funding allocation outcomes of government venture capital?*

The final objective is to examine the investors' ability in distilling high-profile candidates. Investors' decision-making accuracy is questioned by comparing the effects of candidates' characteristics that were used as important selection criteria on desired performance outcomes. As part of the interrogation, the role of resources and capabilities in affecting performance is assessed. Specifically, the objectives entail addressing the following research questions: *How accurate are selection criteria that funding allocation decisions are based upon at explaining long-term performance outcomes of investors and investees? Which configurations of ventures' capabilities affect long-term performance outcomes of investors and investees?*

Synopsis of the Thesis

This project uses real options theory to integrate financial and behavioural perspectives in a unified framework to examine the determinants and outcomes of innovation investments designed to help small firms commercialise their research and development activities. The study examines whether the formal real options reasoning (ROR) structure evident in the composition and execution of the government venture funding programme is also underpinned by the real options logic of decision-making. Real options reasoning lens helps to capture organisational reality, in which the tension exists between economic logic of efficient resource allocation, and behavioural and cognitive effects on rational sense-making.

To investigate government investment patterns, 367 projects from 275 firms that participated in the Small Business Innovation Research (SBIR) programme administered by the National Health Institute in the U.S. were analysed over a seven-year period from 2006 to 2012. Under the staged funding scheme, Phase I initial investment is characterised as a real option, which grants investors the right to make further investment into Phase II or to discontinue funding. The intention was to delineate determinants and outcomes of government venture funding decisions. Investment decisions consistent with ROR were conceptualised as funding allocation outcomes and operationalised as initial commitment, discontinuation, sequencing and fit based on the primary idea that staged investment approach facilitates knowledge creation during R&D activities and leads to commercialisation outcomes. Determinants of funding allocation decision outcomes were analysed from the signalling perspective and comprised five categories of signals: legitimacy, efficacy, capabilities, project appeal characteristics and distortions. The attention-based view was drawn upon to understand whether more observable, more salient and more relevant attributes and categories of signals distort decision-makers' selection and interpretation practices. The performance of new ventures was assessed in terms of their ability to achieve target outcomes of two distinct groups of stakeholders—investors and firms. Hence, the outcomes of investment allocation decisions were measured as investment yield and firm performance related to sales, employment and innovation.

This study finds evidence that government venture funders intuitively follow real options reasoning. That is, the funding initiative is explicitly structured in line with the real options approach that allows extracting value from the staged investments. However, although the structure of the programme is consistent with the characteristics of real options reasoning, the funding allocation decisions are only made in accordance with the real options logic in approximately half the cases, undermining the overall efficiency of the programme. Drawing on signalling and attention-based view helps explain some discrepancies between prescribed and actual investment behaviour. The findings advance the theory of R&D investments in the context of government venture funding and have important research policy implications. The study is believed to be a timely addition to the still rather underdeveloped empirical body of literature integrating financial and behavioural perspectives of ROR. It aids with delineating further boundary conditions of ROR by investigating the choices of government venture capitalists in financing innovation projects of small entrepreneurial firms.

Main Contributions to the Field

This study is known to be among the few to test propositions of real options reasoning in the context of government venture funding. As such, it offers unique insights for a better understanding of the investment logic and behaviour of the capital markets, which has significant repercussions for research, management and public policy theory and practice related to innovation and entrepreneurship. The contribution of the current study is threefold.

Theoretical Contributions

The options approach has been described as a useful strategic tool in making resource commitments with the minimal risks (Chatterjee et al. 1999). Given that allocation of financial resources is a primary task of investors, the project adds to the developing body of work that investigates whether prescriptions of real options reasoning theory has an empirical validity and to what extent their formal and explicit implementation helps enhance performance. The adopted conceptual approach enabled to move beyond the sheer assumptions of the importance of budget as an input to the innovation process and instead examined how resources can be allocated in the most optimal way to yield performance benefits, making a contribution to the literature on strategic management of investment portfolios.

First, to test the propositions of ROR, the study concentrated on a specific empirical context in which funding decisions take place—government venture capital, thereby helping comprehend the normative validity of the theory. The findings confirm that real options reasoning is indeed applicable to a wide range of organisational settings associated with strategic uncertainty and with embedded options, such as investments in innovation projects by public venture capital. However, in spite of the fact that the studied venture capital programme is explicitly structured in line with ROR and encompasses stage-wise sequential investment practices, the structure does not directly translate into a disciplined options-like decision-making approach.

The judgements of public venture capital decision-makers reflect the inconsistent discrepancy between prescriptions of the real options approach and the actual implementation of resource allocation strategies, suggesting that the theory is of high empirical value and offers important practical implications. The results show that when venture capitalists allocate financial resources in line with real options decision-making logic, they gain significant improvements in performance outcomes, whereas deviations from prescriptions of ROR potentially detract from the value offered by a flexible options-like approach. Therefore, the inconsistent use of the real options approach in practice undermines the benefits associated with ROR.

Second, the examination of the organisational practice of the real options approach in the context of government venture capital offers new empirical evidence for the validation and refinement of the descriptive propositions of the theory. To reconcile the understanding of financial and behavioural aspects related to resource allocation strategies, real options theory was complemented with signalling theory and attention-based view, which offered insights into the decision-making process of government venture capital providers. Hence, the study adds to a yet underdeveloped body of literature integrating financial and behavioural perspectives of real options reasoning and helps explain some discrepancies between prescribed and actual investment behaviour. Specifically, insights derived by leaning on signalling theory outline categories of factors that influence investors' perceptions of options' value during the evaluation process. At the same time, the attention-based view suggests that the process of options-like decision-making is subject to the investors' bounded rationality, resulting in evaluation bias.

Finally, the study makes a contribution to the understanding of the role of resources and capabilities in extracting value from sequential stage-wise investments. The results show that configurations of capabilities have complementarity as well as substitution effects on performance outcomes. Such inquiry helps establish the link between economic and decision-making theories, and informs practitioners of the competences necessary for exercising the real options for strategic investment.

Empirical Contributions

The primary empirical contribution of the study is confined to its multi-level conceptual model and measurement instruments. Theoretical propositions were tested on a novel dataset comprising longitudinal secondary data compiled from multiple sources, which aided generation of new insights.

Research applying positivist-induced principles to investigate antecedents and consequences of ROR decision-making has only started to develop recently (e.g. Vassolo et al. 2004; Levitas and Chi 2010). Thus, focusing on the issues relevant to the unique setting enabled developing context-specific variables, thereby significantly enhancing the power of the model analysing the impact of real options decisions on performance (Krychowski and Quelin 2010).

The multi-level model containing established as well as newly-developed variables on firms, projects and individuals allowed for a more fine-grained analysis resulting in a delineation of critical boundary conditions of the tested hypotheses. The split sample analysis showed that firms perform differently depending on whether they previously participated in the funding programme or not. That is, multiple-award holding firms achieved different performance outcomes and required different configurations of skills, resources and capabilities in comparison to their single-award holding peers.

The study makes a distinction between private and social returns by incorporating a multi-stakeholder perspective and assessing the performance of new ventures in terms of their ability to achieve target outcomes of two distinct groups—investors and firms[7]. Whereas the firm's perspective is concerned with determining the worth of the venture, the funder's perspective aims to evaluate the value of the investment by comparing its cost to the desired outcomes. As such, the incorporation of different groups of project stakeholders allowed to make judgements about the performance of new ventures from multiple perspectives and to account for heterogeneous pursued end goals. The findings show that real options approach is predominantly an investment tool, which offers more gains to project funders than to project owners or managers. Additionally, the heterogeneity in statistical effects is explained by the differences in the types of performance outcomes, i.e. sales, employment, or innovation.

Finally, scientific inquiry into resource allocation strategies of public venture capitalists benefitted from studying investments in R&D and innovation at the project-level, as it is deemed the most suitable level of analysis (Link et al. 2014). Overall, focusing on the breadth and multi-dimensionality of measurement and operationalisation instruments through the use of innovative research tools provided the means of grasping a comprehensive picture of issues pertaining to the entrepreneurship research (Brown et al. 2001).

[7] In contrast to the original framework of Zwikael and Smyrk (2012), given that studied firms are nascent ventures, the project manager and project owner present the same stakeholder category.

Managerial and Research Policy Contributions

Finally, the study bears practical contributions. To managers and entrepreneurs, the results help understand the process of how funding allocation decisions are made and which characteristics applicants need to focus on signalling strategically to increase their chances of receiving external financial support.

The study also contributes to the longstanding debate on whether public funding programmes generate sufficient private and social returns to justify their existence and also whether taxpayers' money is allocated in the most efficient way (David et al. 2000; Klette et al. 2000).

Prior scholarly work on the effects of public funding programmes has been dominated by empirical investigations, giving a little theoretical explanation of the phenomena (Kleer 2010). Guided by strong theoretical rationale, the empirical model presented here contributes to the understanding of the extent to which present operational procedures implemented by the government funders promise performance advantages. The understanding of the effect of government venture capital programmes was enhanced by analysing the data on returns from such initiatives (Jeng and Wells 2000).

Also, the evaluation criteria of the government venture funders' decision-making process are scrutinised, which allows for an objective assessment of the overall efficiency of the program and informs policy makers of the apparent weaknesses of such initiatives. Most importantly, the results indicate that the value offered by the government funding programmes gets eroded due to inefficient funding allocation decisions and evaluation bias, whereby an additional unit of government investment does not lead to better stream of social value from the private sector.

1.5 Thesis Outline

The thesis consists of ten chapters. The current introductory chapter presents the rationale for undertaking the project and discusses motivations as well as research and practical problems that laid the foundation for the study. Then, it gives a brief overview of the literature and conceptual underpinnings that enabled identification of theoretical, empirical and research policy gaps, followed by a statement of resulting contributions to the field.

Chapter 2 summarises the main strands of the extant literature on the financing of innovation and entrepreneurship. It starts with an overview of sources of funding available to SMEs and then goes into a detailed discussion of the types of governmental funding programmes, their objectives and shortcomings. Next, the findings from existing studies are categorised by the type of the intended effect. Then, the performance of government venture capital is compared and contrasted with private venture capital and is followed by the discussion of the typical steps and procedures involved in the decision-making process of the venture capitalist. Finally, the effects of sequential investments and resource allocation strategies are reviewed. To conclude, the chapter finishes with a set of specific learnings that set the scene for the development of the conceptual underpinnings.

Chapter 3 presents an in-depth review of theoretical perspectives guiding the direction of conceptual developments underlying the project; namely, real options theory, signalling theory and attention-based view. Rhetorical ideas and formalisations of each theory are discussed, followed by an explanation of how the theory is expected to help address the aims and objectives of the present research. The final section gives an account of the complementary power of selected theories in investigating the phenomena in question.

Chapter 4 is an extension of the theoretical chapter but specifically focuses on developing a set of conceptual propositions and testable research hypotheses under the umbrella of each theory. More specifically, to reflect the adopted theoretical directions, conceptual developments comprise three distinct frameworks. Part I conceptual model uses the real options reasoning lens to present the hypotheses related to the effects of distinct elements of resource allocation strategies on performance outcomes. Part II draws on signalling theory and attention-based view to express a series of conjectures pertaining to the question of which factors affect resource allocation outcomes. Part III is dedicated to exploring the impact of financial decisions and firm-level heterogeneity on performance in a unified framework.

Chapter 5 is focused on explaining philosophical and methodological foundations that informed the development of an analytical approach for the research design. Following the explanation of primary research formulations, procedures related to data collection, database building, operationalisation and measurement of variables, and statistical tools and techniques are described.

Chapter 6 gives an account of the steps taken to convert raw data into a working format, including missing value analysis, imputation procedure and outlier analysis. Next, it sketches out empirical procedures that were carried out to prepare and investigate the data prior to the regression analyses, such as examination of normality, linearity, homoscedasticity, multicollinearity and endogeneity assumptions. To conclude, the chapter presents preliminary exploratory analysis to get an insight into the patterns of the data by examining descriptive and correlation statistics.

Chapters 7 through 9 report results corresponding to Part I, Part II and Part III analyses. Hypotheses are confirmed or refuted in light of the statistical findings. Additional tests are conducted to check for robustness and sensitivity of obtained results. Finally, the main findings are summarised and discussed.

Chapter 10 concludes the thesis by giving a succinct summary of the primary insights of the scientific investigation. Next, the findings are interpreted in relation to the implications that they present to the theoretical, managerial and public policy research and practice. Finally, the chapter outlines any limitations of the study that might have an impact on the understanding of the studied phenomena and finishes with a set of suggestions for future research.

Chapter 2 - Literature on Financing of Innovation and Entrepreneurship

2.1 Introduction

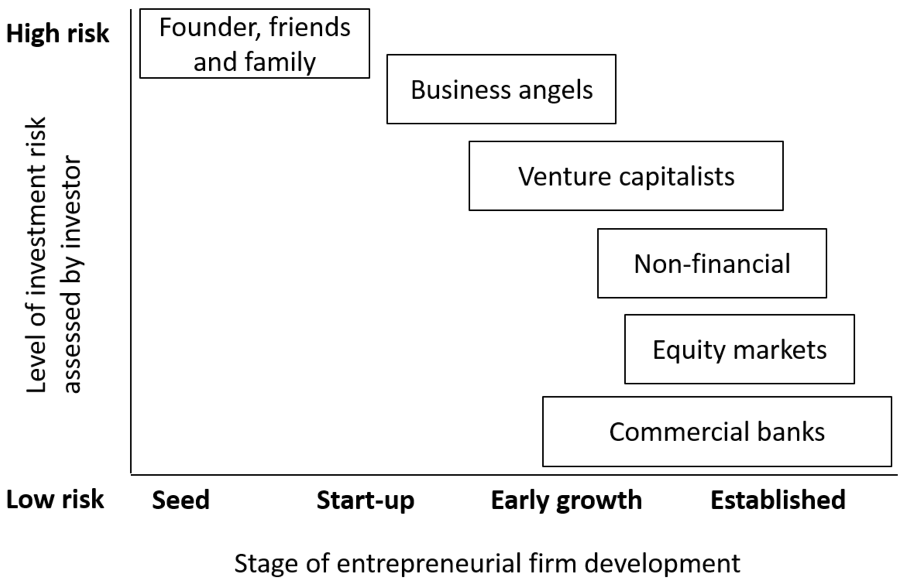
It is important to fund entrepreneurship (Klein et al. 2014). However, funding is problematic due to high uncertainty, agency problems, information asymmetry and moral hazards, which make it difficult to evaluate success chances of innovative SMEs (Lee et al. 2015; Burchardt et al. 2016). Government venture capitalists intervene to support SMEs when private venture capitalists are reluctant to provide early-stage funding. The governmental interventionist programmes are associated with a number of private and social benefits, yet are subject to criticism due to limitations inherent in the evaluation and selection process (Lerner 2010). Resource allocation mechanisms and accurate decision-making criteria are believed to offer a way forward in improving efficiency and optimality of sequential investments into R&D projects by public government funds.

This chapter provides background for the development of conceptual propositions underpinning the present study and summarises the primary debates in the relevant literature domains, making links and drawing conclusions, which helps identify a set of research gaps and unanswered issues.

2.2 Overview of Funding Sources Available to Small and Medium Enterprises

Different stages of venture development are characterised by various levels of risk which, subsequently, affects the ability of nascent firms to access external funding sources. Figure 2-1 demonstrates the providers of funding available to entrepreneurs at different stages of venture development. As the project advances through the stages of development, the level of associated risk diminishes, opening up a wider range of funding sources. At the early stages, however, access to capital is limited. In particular, there is a gap between the seed and the start-up stages, which requires entrepreneurs to rely on personal equity in order to progress the venture to the point that will make it attractive to angel and venture capital providers (Cooper 2003). Angels—wealthy individuals that provide start-up capital to entrepreneurs—are an alternative source of external funding (Gompers 1995; Van Osnabrugge and Robinson 2000). Prior research found that angel investors provide an equivalent amount of financial support to entrepreneurs at initial stages of venture development (Roberts 1991). However, financing by business angels has two primary caveats. First, business angels favour funding deals that require small amounts for venture launch (Freear et al. 1994). Second, the supply of such finance is contingent upon the availability of the slack capital of angels, which is limited in nature (Jeng and Wells 2000). Consequently, although business angels are a suitable substitute for personal equity at initial stages, they are insufficient for early venture development stages. As a result, venture capital is the most suitable form of financing small firm growth.

Figure 2-1: Funding sources at different stages of venture development



Source: Adopted from Van Osnabrugge and Robinson (2000 p.37)

High-risk ventures are associated with higher uncertainty but also high variance for potential returns, which in combination increase information asymmetry between borrowers and lenders (Lee et al. 2007). In contrast to funds offered by banks or raised in the equity markets, venture capital firms are more represented in high-risk industries due to their ability to reduce the cost of information asymmetry through efficient selection and monitoring procedures (Amit et al. 1998). Venture capitalists have specialised expertise and skills necessary to assess the risks of complex technologies and innovations of nascent firms operating in high-tech industries, which neither bankers nor capital markets can do, magnifying information asymmetry problems for the latter (Elston and Audretsch 2011).

In addition to their specialisation in financing risky ventures, venture capital firms exhibit a number of other attributes that distinguish them from other external funding providers (Wright and Robbie 1998). First, venture capitalists make fixed term investments and anticipate no returns from such deals until after their completion (Wright et al. 2005). Puri and Zarutskie (2012) found that nearly half of VC-funded new firms start without any commercial revenues. Second, venture capitalists maintain an active position in the relationship with their borrowers, characterised by the ongoing monitoring and provision of value-added services (Jeng and Wells 2000). Therefore, venture capitalists are frequently viewed as ‘informal capital’ (Lee et al. 2007) or ‘active investor’ (Jensen 1989) due to their involvement beyond the sheer provision of finance. Last, but not least, venture capital firms structure the investment process across a number of stages (Tyebjee and Bruno 1984; Sahlman 1990), with funds being allocated sequentially based on the attainment of milestones (Gompers and Lerner 2000).

Broadly speaking, venture capital firms can be organised as private sector funds and public sector funds, which fall into three dominant categories—independent VC, corporate VC and government VC[8]. The form that venture capitalists take determines their investment patterns, sources of funds, investment targets, screening and evaluation criteria, skills, governance structure, the level of risk-taking, the extent and duration of post-deal involvement as well as overarching funding objectives (Wright et al. 2005; Grilli and Murtinu 2014). For example, Manigart et al. (2002) found that venture capitalists making early-stage deals expect higher returns on their investment than on late-stage deals. Likewise, in contrast to their public sector counterparts, private venture capitalists pursue deals that offer higher returns on investment (Manigart et al. 2002).

As Amit and colleagues (1998) argued, even though venture capitalists' perception of costs associated with information asymmetry is lower than that of other external finance providers, venture capitalists still prefer less risky firms that can provide more information. As a result, venture capitalists favour investments into later-stage ventures over start-up ventures (Amit et al. 1998). Also, the supply of private venture capital is insufficient to support all potentially lucrative technology-oriented ventures. For example, according to Lerner (2002), in 2000 in the U.S. private VCs provided first-time funding to only 2,200 ventures, while each year on average one million new firms emerge. Moreover, provision of VC capital is affected by legal and institutional factors, which differ hugely across countries, making some environments more prone to underinvestment in high-potential small firms (Groh et al. 2010; Jeng and Wells 2000). Finally, evidence exists that private VC is reluctant to fund projects that have extended experimentation stages, which is often the case of emerging high-potential industries such as, for instance, sustainable energy (Nanda et al. 2015). As a result, governments intervene with the provision of public venture capital programmes.

[8] Corporate VCs will not be discussed in further detail in subsequent sections as their organisation differs significantly from independent VCs and government VCs.

Government as Venture Capitalist

Motivations and Objectives of Governmental Interventionist Programmes

Governmental interventionist actions are aimed to address the externalities caused by market failure—private sector underinvestment in socially-valuable R&D as a result of incomplete knowledge appropriability and limited access to finance by the SMEs, triggered by information gaps and high uncertainty (Czarnitzki and Toole 2007; Hsu 2006; Link and Scott 2009).

The key intended positive effects that governmental financial programmes pursue are twofold: stimulate R&D knowledge spillover from the private to the public sector and to certify the quality of small firms to other finance providers, especially in high-tech industries, where conventional financial evaluation instruments convey little information (Lerner 1999; Lerner 2002). Another indirect justification of such programmes relates to the promotion of the economic diversity, which is achieved by giving support to the underrepresented members of the SME sectors (Scott 2000) and neglected industries (Lerner 2002).

The literature uses two lenses to analyse the position adopted by the government in funding SMEs—innovation policy or entrepreneurship policy. Studies using the innovation policy lens argue that the primary objective of the government is to prevent private sector underinvestment in R&D and fund those projects that are considered marginal, i.e. projects that may have low private returns but high social returns (e.g. Wallsten 2000). On the other hand, academics adopting the entrepreneurship policy lens compare the government with a risk-taking entrepreneur that is driven by the same motives as private venture capitalists, i.e. selection of high-profile candidates in order to maximise returns on investment, which in the case of the government are of social nature (Link and Scott 2010). In the first case, the projects are selected based on their economic merit, while in the second case they are based on their likelihood of commercial success (Wallsten 2000).

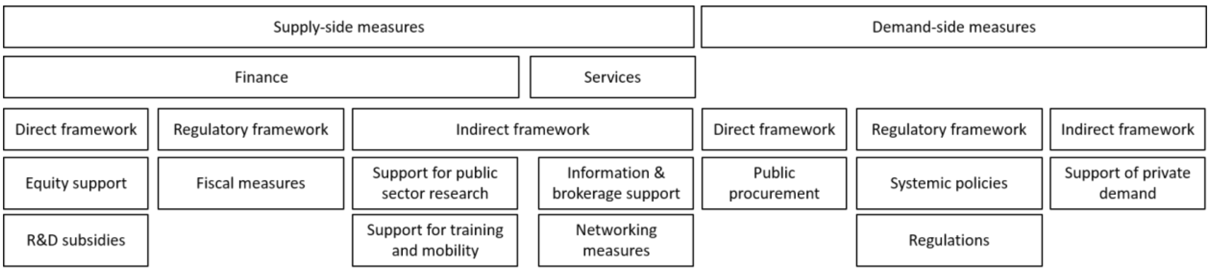
Either way, however, researchers agree that the primary motivation of governments behind the initiation of public venture capital funds and subsidy programmes is to directly intervene with a 'hands-on policy approach' to mitigate the problems caused by market failure, manifested in the lack of provision of private venture capital to support early-stage ventures, which then leads to the shortage of high-quality candidates for late-stage VC funding (Cumming et al. 2014).

Overview of Governmental Interventionist Programmes

Many governments that recognise the insufficient market delivery of financial support for the development of innovation have introduced a spectrum of policy measures. Edler and Georghiou (2007) presented a taxonomy that depicts a range of innovation policy measures (Figure 2-2). Public support to stimulate private sector innovation activities is typically broken down into supply-side and demand-side instruments, with the former focused on the provision of additional inputs for innovation, i.e. tangible and intangible resources, and the latter on the facilitation of production of innovation outputs, i.e. products and services (Aschhoff and Sofka 2009).

Both supply-side and demand-side instruments operate under three broad frameworks—direct, indirect and regulatory (Alperovych et al. 2015; Cumming and Li 2013). Regulatory framework refers to laws that include tax incentives and other institutional mechanisms. Indirect framework relates to support systems for knowledge transfer via universities, laboratories, research clusters and business incubators. Finally, direct framework captures investment programmes, such as guarantee schemes to private VC, public-private syndicates and hybrid co-investment schemes, and subsidies to SMEs.

Figure 2-2: Overview of public support innovation instruments



Source: Adapted from Edler and Georghiou (2007 p.953)

As a result of the presence of multiple instruments that refer to the direct financial intervention programmes, the extant literature lacks an agreement regarding the conceptualisation of government venture capital and a number of definitions prevail (Cumming et al. 2014). The most important distinction concerns the governance mechanism, which differentiates between government-owned venture capitalists (GOVCs) and government-supported venture capitalists (GSVCs) (Brander et al. 2014). Government-owned VCs are entities, initiated and managed by governments via financial instruments, such as financing, tax credits and subsidies (Cumming et al. 2014; Brander et al. 2014). Government-supported VCs are typically private entities in which government is a limited partner or a major investor, or which participate in government programmes to obtain financial support. In other words, the primary difference is that GOVCs are fully funded by the government, while GSVCs are partly funded by the government (Brander et al. 2014).

The present study focuses on direct R&D subsidies by government-owned VC investment funds that are implemented in most OECD countries. The subsidy schemes operate on a competitive basis, whereby firms apply for financial support to develop novel technologies and the government takes on a role of a venture capitalist to select and fund promising R&D projects that would not have been carried out in the absence of public support (Aschhoff and Sofka 2009). Table 2-1 presents a summary of the primary elements that characterise public R&D subsidies.

Table 2-1: Overview of public R&D subsidies

Characteristic	**Public R&D subsidies**
Selection by	State
Primary government objective	Stimulation of R&D activities of firms
Input for firms	Money
Primary participation incentive for firms	Cost/risk sharing
Effect on firm success	Cost reduction
Time horizon	Medium-term
Inherent risk	Crowding out of private R&D investments

Source: Adopted from Aschhoff and Sofka (2009 p.1238)

2.3 Consequences of External Funding on Innovation and Entrepreneurship

Effects of Government Venture Funding on Performance Outcomes

To assess the contribution made by the policy intervention, the literature refers to the concept of additionality of support (Georghiou 2002). Scholarly work differentiates between three types of additionality effects of government subsidies on desired performance outcomes—input additionality (R&D intensity and efforts), output additionality (firm growth and innovation performance) and behavioural additionality (certification, productivity and learning). While measures related to input and output additionality capture long-term performance effects of specific R&D projects, behavioural additionality reflects short-term changes in learning practices (Georghiou 2002). Furthermore, input and output additionalities have been defined as first-order factors, while behavioural additionalities refer to second-order factors (Autio et al. 2008). Table 2-2 presents a summary of the effects of public R&D subsidies on a range of outcomes.

Input Additionality

Input additionality concerns the substitution and complementarity effects of public investment on private investments (David et al. 2000). Public R&D subsidies reduce development costs and raise the anticipated profits, creating incentives for firms to intensify private R&D spending and efforts, which results in input additionality effects (Dimos and Pugh 2016). In the opposite case, when firms reduce the private spending after receiving public support, the crowding out effect occurs.

A number of review papers concluded that the extant literature provided contradictory findings concerning the effect of government subsidies, showing that public subsidies complement private R&D, have no effect at all, or crowd-out private R&D (Klette et al. 2000; David et al. 2000; Dimos and Pugh 2016). For instance, Wallsten (2000) found that government-financed firms reduced their own internal R&D spending in the years immediately following the award. Goolsbee (1998) noted that larger government grants directly increase salaries of R&D workers, thereby crowding out internal R&D efforts. However, recent studies have generated results using more robust methods and datasets, and explicitly accounting for potential endogeneity issues, which lean towards the absence of the crowding-out effect. A new meta-analysis by Dimos and Pugh (2016) rejected the hypothesis that public subsidies crowd out private investment but found no evidence of substantial additionality, suggesting that in general public funds are associated with both increased input and output additionality, thereby correcting for market failures, although their effects diminish with time.

Table 2-2: Effects of financial support of government venture capital on firm performance

Category & Definition	Consequence	Effect of R&D subsidies	Direction of effect[9]	Source of findings[10]
Input Additionality Continued efficiency in R&D process by the firms after receipt of public subsidies (Clarysse et al. 2009)	Continued internal R&D intensity & efforts	Increased or stable level of R&D spending by the firm	+	Beck et al. 2016; Aerts and Schmidt 2008; Czarnitzki and Lopes-Bento 2013; Dimos and Pugh 2016; Gonzalez and Pazo 2008; Hottenrott and Lopes-Bento 2014; Hud and Hussinger 2015
	Crowding out of private funds	Reduced level of R&D spending by the firm	-	Wallsten 2000; Boente 2004; Goolsbee 1998
Output Additionality The proportion of outputs from the R&D process attributed to public subsidies (Georghiou 2002)	Knowledge spillover	R&D spillovers	/ & +[11]	Boente 2004
	Firm growth	Sales growth	+	Lerner 1999; Howell 2015
		Employment growth	+	Lerner 1999; Link and Scott 2012; Link and Scott 2013
			/	Wallsten 2000
		Greater survival rate	+	Lerner and Kegler 2001
		Profitability (return on assets)	+	Bayona-Sáez and García-Marco 2010
	Commercialisation of innovation	Number of patents	+	Radas et al. 2015; Howell 2015
			/	Bertoni and Tykvova 2015
		Quality of patents	/	Bertoni and Tykvova 2015
Behavioural Additionality Changes in the behaviour of other market actors towards the SME induced by public subsidies (Georghiou 2002; Meuleman and De Maeseneire 2012)	Certification / Halo effect	Positive signal to private investors or banks to stimulate influx of subsequent external funding	+	Lerner 1999; Feldman and Kelley 2006; Meuleman and De Maeseneire 2012; Soederblom et al. 2015; Toole and Czarnitzki 2007; Kleer 2010; Leleux and Surlemont 2003; Howell 2015; Feldman and Kelley 2006; Brander et al. 2014
		Positive signal to potential employees for accessing human capital	+	Soederblom et al. 2015
	Impact on career choices and academic entrepreneurship	Direct and demonstration effect on stimulating commercialisation behaviour of knowledge workers	+	Audretsch et al. 2000b; Audretsch et al. 2002b, Audretsch 2003, Toole and Czarnitzki 2007
	Efficiency	Productivity improvement	-	Alperovych et al. 2015
	Learning	Intra- and inter-organisational learning imposes a positive effect during the first financed projects, but it diminishes the more projects are financed	+ & -	Clarysse et al. 2009
	Capability building	Strengthened absorptive capacity	+	Radas et al. 2015

[9] + refers to the positive effect, - refers to the negative effect, / refers to no effect.
[10] The list of sources of findings is not exhaustive, but indicative.
[11] No effect was found in the total sample and low-technology industries, but weak positive effect was observed in the high-technology industries.

Output Additionality

The studies concerned with evaluating output additionality investigated whether the alleviation of financial constraints with the provision of public subsidies stimulates the development of an entrepreneurial economy. Link and Scott (2010) demonstrated that small firms invest below the private hurdle rates because external capital providers face high perceived technical and market uncertainty.

Empirical evidence showed that R&D subsidies minimise private R&D underinvestment stemming from financial constraints by mitigating product market uncertainty (Toole and Czarnitzki 2007). As such, support for public subsidies corrects for the private market failure of underinvestment in socially-valuable fields and stimulates commercialisation from research (Audretsch, Link, et al. 2002). Moreover, Link and Ruhm (2009) confirmed that government subsidies are also crucial for projects that eventually reach the commercialisation stage. Feldman and Kelley (2006) concluded that the absence of public subsidies prevents firms from continuing high-risk high-potential R&D projects. All in all, government grants are critical sources the firms draw upon to reduce capital shortage at early development and growth stages (Elston and Audretsch 2011).

Yet another research strand concentrated on examining the effects of subsidies on the direct firms' performance. Lerner (1999) investigated the effects of the government VC initiative on the long-term performance of high-tech ventures. The author found that government-VC-financed firms achieved higher sales and employment growth and were more likely to receive private VC in the years to come in comparison to the firms that did not receive subsidies, but such effects were *only* applicable to the firms located in regions with high concentration of VC capital and from high-tech industries. The finding implies that the allocation of the award per se has no effect, but instead is contingent upon other factors (Lerner 1999). The effect of larger or additional awards on performance was insignificant, suggesting the mere certification role of R&D grants.

A recent study by Howell (2015) confirmed the positive effect of early-stage government subsidies on the likelihood of receiving subsequent venture funding, patenting, revenue growth and successful exit via IPO or acquisition, but found no positive spillover effects of subsidies. However, in contrast to Lerner (1999), Howell (2015) concluded that it is not the certification effect of grants that increases the probability of attracting future external funding, but the prototyping effect—reduction of investors' uncertainty as a result of undertaking proof-of-concept work. As such, funding is helpful in conducting preliminary tests on the viability of technology for subsequent development, which reduces information asymmetry and agency problems. This finding is consistent with the proposition of Toole and Czarnitzki (2007). Taken together, the results of the author suggest that early-stage grants dedicated to prototyping are more beneficial than larger follow-on funds (Howell 2015).

However, despite the numerous positive effects of subsidies identified in prior studies, evidence exists that public funding programmes are subject to a number of problems. For instance, in his paper, Lerner (1999) found that distortions exist in the award allocation process and questioned the effectiveness of the practice of government VCs to allocate larger awards to a few firms as well as to make geographically disperse allocations. In the similar vein, using data on the SBIR programme, Wallsten (2000) found that firms with more employees and patents received more R&D subsidies, but these subsidies did not increase employment growth. More recently, Howell (2015) indicated that the ranks within a competition allocated by government officials are unrelated to market outcomes, suggesting that (i) public venture capitalists fail to distill high-quality candidates from the pool of applicants and (ii) external investors do not perceive grants as signals of firms' superior quality. Overall, these insights from the extant literature point out that public funding programmes may be regarded as Pandora's Box as much as Panacea.

Behavioural Additionality

Additionally, the benefits of the government venture capital programmes are linked to stimulation of the entrepreneurial economy by changing the behaviour of knowledge workers (Audretsch, Weigand, et al. 2002). The results of the survey and the case studies conducted in the U.S. showed that public grants help many firms to start up (Elston and Audretsch 2011; Cumming and Li 2013) and stimulate academic knowledge commercialisation (Audretsch, Weigand, et al. 2002). Toole and Czarnitzki (2007) in their study confirmed that the SBIR programme fosters academic commercialisation behaviour and, hence, can be viewed as an entrepreneurship policy. Overall, SBIR awards are believed to promote entrepreneurship, venture capital, and innovation (Cumming and Li 2013).

A number of studies highlighted the importance of a combination of public and private funding in accelerating commercialisation and entrepreneurship behaviour. For instance, Link et al. (2014) indicated that 17% of all ventures that received SBIR funding subsequently attracted private capital. Hsu (2006) showed that government-funded (SBIR) firms that later received VC funding had a higher likelihood of an R&D alliance and an IPO in contrast to those government-funded firms that did not receive VC funding. Similarly, Link and Ruhm (2009) provided evidence that additional investments from external sources increase the likelihood of innovation commercialisation spurring from later-stage government awards. Recent studies tested the complementarity effect of different sources of external funding and found that investment level and exit performance are highest for the firms that have mixed private and government funds, followed by private funds alone and then government funds alone (Brander et al. 2014; Cumming et al. 2014).

The literature on VC funding has attempted to distinguish between financial and value-added support of different investor types and investigated their impact not only on firms' direct outputs (Brander et al. 2014; Cumming et al. 2014) but also on intermediate operational performance, expressed as efficiency and productivity improvement (Chemmanur et al. 2011; Croce et al. 2013; Alperovych et al. 2015). The findings demonstrated that performance improvement of GVC-backed firms is debatable.

In particular, efforts have been made towards understanding the differences in performance between public and private fund holders. More precisely, literature has shown that government-financed firms achieve lower or no sales growth, employment growth and IPO performance in comparison to their private-VC-financed firms (Grilli and Murtinu 2014; Cumming et al. 2014). On the other hand, Hottenrott and Lopes-Bento (2014) found that public finance enhances innovation performance of SMEs, measured by radical novelties, as much as private finance. Beck et al. (2016) extended this insight by clarifying that in relation to private VC, government VC enhances innovation performance of radical innovations only, but has no impact on incremental innovations.

More recently, academic attention has been diverted to the effect of VC funding on firm efficiency, a metric related to operational performance, which is one of the core mechanisms behind sales and employment growth (Bottazzi et al. 2008). Boente (2004) demonstrated that in comparison to privately-financed projects, publicly-financed projects have no productivity-enhancing effects of R&D spillovers. Chemmanur et al. (2011) and Croce et al. (2013) found that VC-financed firms have higher productivity than their non-VC-financed firms, which may be due to the rigorous selection and evaluation criteria used by VC firms. Further to these studies, Alperovych and colleagues (2015), analysed the effects of different types of VC funding inclusive of government programmes on firms' efficiency in Belgium. The authors found that although firms' efficiency increases as a result of VC investment, this effect is inconsistent across different VC types, with private-VC-funded firms outperforming their government-VC-funded peers in terms of productivity. While there are no observed differences in post-investment productivity levels of private-VC-funded and non-VC-funded firms, government-VC-funded firms significantly lag behind both. Overall, the results suggest that private VC improves the productivity of funded firms, but government VC hinders the improvement in productivity.

Heterogeneity in Effects of Government Venture Capital versus Private Venture Capital

The type of ownership is the most prominent characteristic of the organisational structure of VC firms that can have a profound role in explaining the heterogeneous performance of VC-backed firms (Da Rin et al. 2013). Nonetheless, within the abundant literature on venture capital, the studies analysing the effects of different types of VC ownership and structure on the growth of high-tech ventures remain relatively scant (Grilli and Murtinu 2014). In their paper, Grilli and Murtinu (2014) summarised the potential reasons that might explain the variance in performance of government-VC-backed firms versus private-VC-backed firms.

First, although both government VCs and private VCs share the same goal—to stimulate the growth of small high-potential firms—their final objectives are different. Whereas government VCs aim to foster innovation within the SME sector to increase economic growth and amplify social returns from private R&D efforts, private VCs are driven by profit-maximisation incentives and strive to increase the value of ventures for the initial public offering (IPO) or acquisition (Chemmanur et al. 2011). The study by Jeng and Wells (2000) found that government-funded venture capital is not as strongly determined by IPOs as non-government funded venture capital, and places greater focus on funding early-stage ventures that would otherwise have no access to private finance providers. Overall, the functioning of private venture capital firms is strongly determined by contractual, financial and reputational obligations towards their fundraising sources (Bottazzi et al. 2008). Government VCs are largely exempt from such pressures: since they use public monies to sponsor their activities and supply of these is practically unlimited, sound performance of portfolio firms is not a priority as follow-on funds do not need to be raised (Alperovych et al. 2015).

Second, the extent of direct involvement or value-added services provided by the government VCs may be low, or, if at all present, may be counterproductive due public officers' paucity of expertise in identifying and supporting high-potential ventures and the non-profit driven incentive system (Leleux and Surlemont 2003).

Third, private VCs adhere to the role of an active investor and vigorously monitor the progress of firms they back up financially (Gompers and Lerner 2000), with the aim to account for the potential agency and hold-up problems (Kaplan and Stroemberg 2004). Government VCs do not scrutinise the track record of applicants to the same degree as private VCs (Lerner 2002). Moreover, in contrast to private VCs, their government-managed peers engage in a less elaborate range of post-investment activities and place less emphasis on such value-added services as the development of the business idea, professionalisation and exit orientation (Luukkonen et al. 2013).

Fourth, private VCs and government VCs differ in terms of their perceptions of risk, which explains their preference for certain types of deals. While private venture capitalists favour lower-risk later stage candidates (Amit et al. 1998), government VCs exhibit less risk-aversion by providing support for underdeveloped early-stage ventures and by giving them a chance to come of out shadow, recognising that their activity may eventually yield potential social returns (Grilli and Murtinu 2013).

Finally, government venture capitalists are more prone to influences of political and interest groups in their networks, which can distort the rational selection and evaluation processes, resulting in biassed decision-making (Lerner 2002).

2.4 Antecedents of External Funding on Innovation and Entrepreneurship

Venture Capital Decision-Making

The persistently high failure rate among new ventures makes screening and evaluation of applicants for funding an extremely difficult task (Lerner 2002). Yet, it is also an activity that enables venture capitalists to create value (Alperovych and Hübner 2013). Given that new ventures applying for external funding exhibit significant variation in the quality and nature of their characteristics and pursued opportunities, some will be more qualified to receive financial support than others (Eckhardt et al. 2006). Therefore, evaluation and selection criteria are used to make the judgements about the ventures' viability.

Venture capitalists follow stringent selection criteria to scrutinise candidates and business plans to assess the potential of technology and management (Tyebjee and Bruno 1984; Macmillan et al. 1985; Desarbo et al. 1987; Macmillan et al. 1987). Table 2-3 presents a summary of the criteria ranked as the most important among the venture capital firms. Although the business plan allows assessing to some degree the feasibility of the proposed technology (Lerner 2002), evidence shows that it is the quality of the entrepreneurial team that bears the highest weight on the funding decision (Macmillan et al. 1985). Given that the markets for technology do not always develop as anticipated, the experienced entrepreneurial team is believed to be able to take existing opportunities in new potentially profitable directions (Lerner 2002).

Table 2-3: Summary of the evaluation criteria used by venture capitalists

Category	Characteristic
Entrepreneur's personality	Evaluates risk well
	Capable of sustained effort
	Articulate in discussing venture
	Attends to detail
Entrepreneur's experience	Relevant task record
	Demonstrated leadership ability
	Familiar with market
Characteristics of product/service	Product protectable
	Product has market acceptance
	Prototype developed
Market characteristics	Product stimulates existing market
	Market has high growth rate
	Low threat of early competition
	Venture capitalist familiar with an industry
Financial considerations	Ten times investment in ten years or less
	Highly liquid investment
Venture team composition	Functionally balanced team essential

Source: Adapted from MacMillan et al. (1985 p.127)

Adherence to strict evaluation process allows venture capitalist to reduce information gaps associated with the quality of candidates prior to making an initial financial commitment (Knockaert et al. 2006). After the first infusion of capital into the venture, VC firms stay actively involved and employ a range of monitoring and controlling mechanisms (Macmillan et al. 1989; Bottazzi et al. 2008), one of which is staging of capital investments[12] (Lerner 1995).

Multi-stage venture capital process allows to portion uncertainty and thereby addresses the need for flexibility (Lerner 2002). Subsequently, evaluation and selection of new ventures also occurs at multiple stages and is path-dependent in nature, signifying that later-stage decisions are dependent on the prior-stage decisions, yet may be based on different criteria and be contingent upon new information or new priorities (Eckhardt et al. 2006).

Quality of the evaluation, monitoring and control processes, as well as venture capital firms' proficiency in structuring and conducting such activities are the necessary conditions for efficient resource allocations, which are expected to lead to superior productivity and efficiency of VC-financed firms (Chemmanur et al. 2011; Croce et al. 2013; Alperovych et al. 2015).

[12] Discussion of sequential investments is subject of the next section.

Weaknesses of Government Venture Capital Decision-Making

Government venture capitalists follow the same selection and evaluation process and evaluate applicants based on their technical and commercial potential (Hsu 2006). However, evidence exists that governmental VC programmes are more susceptible to selection issues. Despite the fact that governmental programmes pursue beneficial end goals and often allocate experts to carry out the selection process, who might be even better equipped to deal with technical information than private VCs, evaluating the potential of young ventures in high-tech markets is extremely complex (Lerner 1999). Due to the apparent flaws of the resource allocation processes, public sector investments have been the subject of criticism (Lerner 1999) and described as *"gambles with the public's monies"* (Link and Scott 2009 p.264).

The primary concern surrounding the efficient functioning of public venture capital programmes is related to the effects of institutional and political settings that may introduce distortions to the investment decision-making process based on non-economic criteria (Lerner 2002). More specifically, politicians and other interest groups may exhibit rent-seeking or opportunistic behaviour (Lerner 1999) that may be manifested in a number of ways.

First, government programmes are driven by the internal research agenda and allocate awards to firms that address research or geographic priority areas, even when such firms are unlikely to achieve better long-term performance. The scepticism about the benefits of public subsidies then pertains to the questionable ability of government venture capitalists to select viable candidates that forego funding by private sources as a result of market imperfections and not because they present a low-potential investment opportunity (OECD 1997).

Second, bureaucratic decision-makers may be inclined to 'cherry-pick' candidates to portray the programmes as 'effective' and thereby also enhance their own credentials in the eyes of the public (Dimos and Pugh 2016). As a result of the selection bias, some firms get awards even if they would have succeeded in innovation or commercialisation activities in their absence (Wallsten 2000; Audretsch, Weigand, et al. 2002).

Third, governmental programme officials frequently support politically influential firms, whereby a disproportionate amount of financial resources is allocated to ventures that have already received a large number of awards and have had low commercialisation record[13] (Lerner 1999).

Taken together, a combination of poor selection, monitoring and control practices of government agents results in the investments in unprofitable ventures (Lerner 2002), undermining the efficient and optimal resource allocation of public funds (Lerner 2010; Dimos and Pugh 2016).

[13] In the context of the SBIR programme, such firms have been labelled 'SBIR mills' (Lerner 1999).

2.5 Sequential Venture Capital Investments as a Funding Pattern

Many organisational strategic decisions, such as new product development, market expansion or mergers and acquisitions, are carried out in a sequence of steps (e.g. Kogut and Kulatilaka 1994a; Folta and Miller 2002). Such decisions unfold as a result of an iterative process of information acquisition through learning and experimentation (Guler 2007a). Staged financial allocations and resource endowments enable continuing evaluation of projects' potential, which shapes organisations' course of action and limits associated risks (Guler 2007b). The venture capital industry presents a suitable setting for examining the process of sequential capital allocations because investors make a number of staged investments in new ventures to manage uncertainty and maximise their returns (Sahlman 1990; Lerner 1994; Gompers 1995). Given high levels of ex-ante uncertainty associated with R&D projects that only experimentation can resolve, the nature of VC investments encourages making multiple early bets, which helps delineate a few lucrative investments generating yields (Kerr and Nanda 2014).

Venture capital investments are associated with two primary problems–information asymmetry and agency costs (Gompers 1995). Staged funding is used to mitigate such problems and benefits both investors and firms (Neher 1999; Wang and Zhou 2004). For investors, the management of the investment process through sequential funding allows reducing endogenous uncertainty related to projects and entrepreneurs (Guler 2007a). Ongoing accumulation of project-specific information through sequencing helps investors assess costs and benefits of the project as well as monitor entrepreneurs' effort and opportunistic behaviour. As a result, investors have a strong intention to make timely investments in order to obtain relevant information (Li 2008). For entrepreneurs, staged venture capital financing allows to focus on developing new products and technologies and growing the firm, maximising firms' chances of survival (Dean and Giglierano 1990).

Specifically, in the investment context, sequential funding allocations involve incremental monetary commitments over an extended period of time and at different stages of the project's life cycle (Dixit and Pindyck 1994). Three attributes characterise sequential investments: (i) no yields can be appropriated prior to the completion of the project; (ii) costs and benefits of the project are uncertain; (iii) investors have to balance a portfolio of projects that vie for considerable resources (Guler 2007b). Each investment has an opportunity cost, so investors have to make a trade-off between making an investment in existing projects in order to acquire more information on their potential or switch to new alternative projects (Guler 2007a).

Assessment of potential returns from competing investment opportunities is complicated by the fact that information on alternative projects is obtained over time, yet decisions have to be based on currently available information (March 1991). Thus, new information that regularly arrives due to the staged nature of investments offers the means for investors to update their perspectives on projects' chances of success and make timely continuation or termination decisions (Guler 2007b).

Although sequential funding allocations offer a flexibility advantage and limit downside risks by preventing investors from making excessive capital commitments, such gains are contingent upon the venture capitalist firms' ability to modify investment patterns in response to up-to-date information (Coff and Laverty 2001). Technically, the decision whether to continue subsequent funding allocations should reflect the likelihood of the project succeeding in the future (Dixit and Pindyck 1994; Gompers 1995; Bergemann and Hege 1998); however, in the real life scenario, investors have a number of challenges managing the sequential investment process (Coff and Laverty 2001).

Recent studies on investment patterns in the venture capital industry found that investors exhibit escalated commitment to investments and systematically neglect new information received through a sequential process indicating diminishing anticipated returns (Guler 2007b; Guler 2007a). The results suggest that venture capital firms are prone to making inefficient funding termination decisions that may be triggered by biassed decision-making, agency problems as well as institutional and political influences, making them subject to moral hazards—the primary issue that sequential investments aim to solve (Guler 2007b).

Effects of Resource Allocation Strategies on Performance Outcomes

Resource allocation strategies underlying sequential capital investments comprise initial decision-making and adaptive decision-making. Adaptive decisions are made following the implementation of initial plans and are characterised by the increased emphasis on decision-makers' attention and less procedural rationality (Klingebiel and De Meyer 2013). Organisations implementing sequential projects are faced with the challenge to allocate resources in such a way that makes it possible to combine the efficient delivery of plans with any necessary adaptations (Eisenhardt et al. 2010; Lewis et al. 2002).

Flexibility in resource allocation is a crucial aspect for entrepreneurial firms to create value under dynamic market circumstances (McGrath 1999). Such flexibility enables firms to concurrently explore a window of scenarios and pursue subsequent implementation of the most promising ones (Sanchez 1993). However, flexibility also limits the firms' ability to stabilise plans and make strategic commitments (Ghemawat and Costa 1993; Sull 2003). The options-like investment decision-making is one such approach that helps organisations balance the intended plans with flexibility in resource allocation (Reuer and Tong 2007).

Organisations use a number of strategies to allocate resources to a portfolio of innovative projects and combine elements such as breadth, selectiveness, sequencing and magnitude. Breadth denotes the concurrent allocation of initial resources to a number of alternative projects at earlier stages; selectiveness and sequencing refer to resource reallocation strategies at later stages and indicate intentional pruning of the portfolio; the magnitude of resource allocation reflects the size of investment commitment and the level of project resourcing (Klingebiel and Rammer 2014; Klingebiel and Adner 2015). Existing literature on project portfolio management indicates that organisations exhibit heterogeneity in strategic implementation of resource allocation for product development (Griffin 1997; Hauser et al. 2006).

Strategic resource allocation elements shape the scope of innovation projects, the size of the overall portfolio as well as project development duration (Klingebiel and Rammer 2014). Research evidence exists that various resource allocation mechanisms have a differential impact on performance outcomes of innovative projects, suggesting that it is not the quantity of resources per se, but rather the quality of resource allocation decisions that enhance innovation performance (Klingebiel and Rammer 2014). Adaptive resource allocation strategies are associated with improved overall long-term performance, allowing to contain costs and respond to unravelling contingencies (Klingebiel and De Meyer 2013).

Greater breadth of resource allocations positively affects anticipated performance in a number of ways. First, it allows to simultaneously place bets on multiple innovation projects that can potentially target a variety of customer markets (Sorenson 2000). Second, it stimulates information search, which is known to enhance new product development decision-making and activities (Leiponen and Helfat 2010). As a result, the likelihood of innovation success increases.

Termination of projects under development is not valuable in all situations. However, as the firm reduces complexity and uncertainty by exploring a broad spectrum of opportunities, selectiveness is necessary at later stages, which call for more extensive resource commitments (Pich et al. 2002; Sommer and Loch 2004; Loch et al. 2008; Sommer et al. 2009). In other words, while breadth is inexpensive at early stages, its benefits diminish over time as the costs of development surge (Klingebiel and Rammer 2014). Selectiveness allows firms to respond to new contingencies that arise during the early stages and to withdraw resources from failing initiatives in favour of the more commercially viable ones. Sequencing is an attribute of dynamic allocation regimes where innovation endeavours are developed iteratively through the trial and error process (McGrath and Nerkar 2004). The sequencing logic forms the basis of the new product development funnel models, whereby a multitude of opportunities are sieved through at early stages through explorative research and result in a small number of products that merit commercialisation efforts (Ding and Eliashberg 2002; Khurana and Rosenthal 1997; Cooper 2008).

At present, the literature strand that addresses how distinct resource allocation strategies affect performance outcomes is limited. The results of Klingebiel and Rammer (2014) show that the breadth of initial opportunities has a stronger positive impact on innovation performance than the magnitude of project investments. Allocating smaller funds to a portfolio of projects is more beneficial than allocating larger lump sums to individual projects. Therefore, fewer resource allocations per project enable to explore more uncertain opportunities with minimal risks (Klingebiel and De Meyer 2013). Moreover, the authors found that performance gains are more profound among the firms that match broad initial allocation of resources with late-stage selectiveness, and this effect is strongest among the firms pursuing more novel innovation projects. Another study by Klingebiel and Adner (2015) found no direct impact of the magnitude of initial project investment and discontinuation on innovation performance, yet sequencing had a positive effect on new product sales. Guler (2007b), however, provided evidence that the high number of financing rounds lowers the odds of success and the magnitude of anticipated returns, suggesting that venture capital firms can appropriate the maximum value from fewer rounds of investments in each venture. Overall, the research shows that although sequencing is beneficial, its rate ought to be low and guided by disciplined selectiveness criteria. The findings provide support for wider strategic literature that posited that organisational performance is enhanced by learning via low-cost probes (Brown and Eisenhardt 1997), entrepreneurial failure (McGrath 1999) and funnel-style innovation (Ding and Eliashberg 2002).

2.6 Critical Observations and Research Opportunities for the Current Project

Following the work of Lerner (1999), the view adopted in the present study refers to the government as a public venture capitalist. Kortum and Lerner (2000 p.676) defined venture capital as *"equity or equity-linked investments in young, privately held companies, where the investor is a financial intermediary who is typically active as a director, an advisor, or even a manager of the firm".* Therefore, when the government provides financial support to nascent firms for the development of R&D initiatives, it follows the same rationale as private venture capital.

The studies by Link and Scott (2009; 2010) showed that the probability of commercialisation by firms that received R&D subsidies in the U.S. is on average 50%, but the results among the firms are widely spread, ranging from 0.1% to 100% probability of commercialisation. These findings suggest the entrepreneurial role that the government takes on by accepting the uncertainty related to the fact that half of the funded projects will fail to reach the market. Such position is shared by other studies that have utilised the entrepreneurial framework to analyse public sector initiatives (Zerbinati and Souitaris 2005).

More specifically, the primary point of interest in the present study is government-owned venture capital, which is often affiliated with federal departments and agencies and is fully funded by public monies. Such programmes make direct equity-like[14] investments in nascent innovative firms (Lerner 2002).

Although R&D subsidies are not distributed through venture capital funds (Brander et al. 2014), they are still often referred to as government venture capital because of a number of similarities they share with private venture capital. First, both private and public funding schemes are highly competitive, as demonstrated by the low 'success rate' of later-stage awards (Hsu 2006). Second, the level of offered financial support is comparable, as is the age of ventures at the time of application (Lerner 1999). Furthermore, both private and public VC follow the same selection and evaluation process to make sequential infusions of capital in risky projects with uncertain payoffs. In particular, the certification justification for the existence of public venture capital awards makes it an imperative that the governments select high-quality as opposed to marginal candidates (Lerner 2002).

Nonetheless, government VC is often criticised for funding a significant number of underachieving firms (Lerner 2002). Given that R&D subsidies are non-repayable, low-quality firms may be encouraged to apply (Czarnitzki and Toole 2007). Hence, if the government funders are unable to select promising firms, it renders public financing programmes counter-productive (De Meza 2002; Lerner 2002). Overall, it was argued that to screen out potentially underachieving firms, government officials should focus more on the rigorous selection process, which entails a thorough consideration of factors that accurately predict venture's success, such as the experience of the management team and strategic clarity of technology development plans (Lerner 2002). Moreover, Feldman and Kelley (2006) suggested that to maximise social rates of return, government venture capital programmes should specifically include selection criteria that assess project's potential for knowledge spillovers.

A persistently high proportion of investments that have no private or public payoffs stresses the importance of efficient venture selection and evaluation, as well as the execution of investment decisions in enhancing the performance of VC firms, which is measured in terms of the yields on each investment (Guler 2007b; Guler 2007a).

As Guler (2007b) observed, although the scholarly work covering various aspects of VC investments is prolific, sequential investments have received the least attention and the studies in this domain have predominantly focused on agency and moral hazard problems (Sahlman 1990; Admati

[14] In contrast to the private or corporate venture capital, government venture capital programmes such as SBIR have no equity stake in the firms they fund and also no right to appropriate their intellectual property (Lerner 1999). Instead, the funds are provided as a grant, contract or subsidy (Lerner 2002).

and Pfleiderer 1994; Gompers 1995; Bergemann and Hege 1998). In particular, the review of the literature has not identified any papers that questioned the efficiency of various resource allocation strategies available within the sequential investment process in the VC setting, neither private nor public. The present study aims to address this gap and investigate resource allocation strategies and candidate evaluation and selection practices of a specific type of VC—government venture programmes.

2.7 Concluding Remarks

The present chapter started off with an overview of funding sources available to small entrepreneurial firms to finance innovation and then concentrated on discussing the specific role of the venture capital in financing entrepreneurship. Next, an account was given of the structure, motivations and goals of a specific type of venture capital—government funds. Then, the extant literature investigating the effects of government funding programmes was summarised, and the most significant findings highlighted, followed by a discussion of notable performance differences between private- and government-funded-VC firms. Following an in-depth review of consequences of public funding, attention was drawn to antecedents of financing outcomes; namely, discussion of the evaluation and selection process that venture capitalists go through and the limitations specific to the decision-making of government venture capital. Further to that, the nature of sequential investments was described, finishing off with the analysis of the effects of differential resource allocation strategies. The chapter concludes with a series of learning points relevant for the current project.

Chapter 3 - Theoretical Perspectives on Antecedents and Outcomes of Venture Funding

3.1 Introduction

The key questions that the current research project aims to address are: 'what effect do various funding decisions have on investment yield and long-term firm performance in the context of government venture capital?' and 'which factors affect funding allocation outcomes and what is their association with performance outcomes?'.

Given the role that the government has in selecting attractive projects and allocating financial resources to them, the current study takes a project funders' perspective. It postulates that real options reasoning investment logic underlying project evaluation processes will impact outcomes of funding allocation decisions and that funders will attend to signals to minimise information asymmetry associated with assessment of innovation projects. Moreover, the aim is to examine whether signalling theory is affected by an attention-based view, whereby more salient signals distort funders' attention from the signals of legitimacy. In addition to investigating separate effects of real options reasoning and signalling theory in the context of government venture capital, the project takes on a challenge to merge these theories in order to examine whether legitimacy signals used as selection criteria for funding allocation decisions are also accurate predictors of desirable investment outcomes.

Theoretical positions underpinning the present research are schematised in Figure 3-1. The study seeks to explore whether the real options structure exhibited by the staged nature of the venture capital programme is also reflected in the decision-making logic of government venture funders in relation to R&D investments. Therefore, an adoption of a combination of real options reasoning, signalling theory and attention-based view helps to reflect different tensions of organisational reality, while complementarity of theories aids in understanding how choices made during decision-making affect achievement of efficiency goals. The inverted pyramid displays the role of theories in a studied setting, in which ROR logic predominantly guides the investment process, and is supported by sense-making, with signals influencing the process of decision-making and attention-regulating mechanisms influencing outcomes of decision-making. Table 3-1 presents a summary of the primary theoretical assumptions underpinning theories employed here, while Table 3-2 outlines how adopted theories dovetail and apply to the research context. Theoretical underpinnings are explained in more detail in the following sections of the chapter, finishing with the discussion of their relevance and complementarity to the study.

Figure 3-1: Theoretical schemata underpinning the current research project

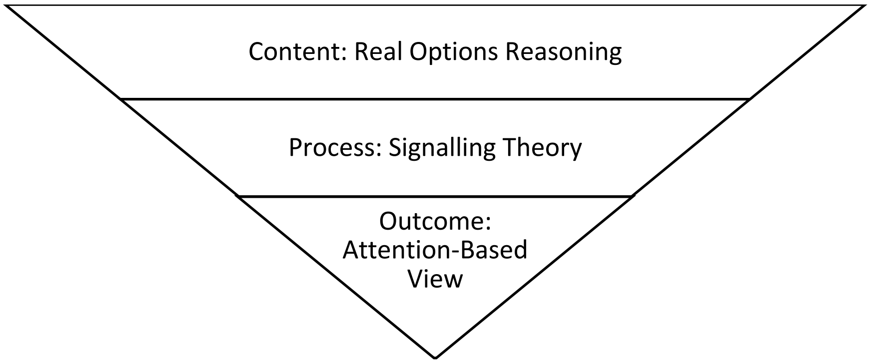


Table 3-1: Description of theories

Theory	Description & main tenets	Key manifestations & dimensions	Primary theoretical papers	Exemplary empirical studies
Real Options Reasoning (ROR)	ROR uses an options-based view to describe investment decision-making process. Real options investments are characterised by sequential, irreversible resource commitments made under conditions of uncertainty (Dixit and Pindyck 1994).	The process of creating a portfolio of options entails the following steps: (1) funder invests in a number of options to create a portfolio; (2) funder preserves the right to exercise those options when a significant portion of uncertainty about the project has been resolved; (3) funder turns attention to signals about the current value of the option to minimise the level of perceived uncertainty; (4) funder either extends or abandons the option based on new information.	McGrath 1997; McGrath et al. 2004; Adner and Levinthal 2004b; Driouchi and Bennett 2012	McGrath and Nerkar, 2004; Li and Chi 2013
Signalling Theory	Signalling theory is concerned with how two parties resolve information asymmetries about underlying qualities. Quality refers to signaller's unobservable ability to fulfil the needs of a receiver of a signal (Connelly et al. 2011).	The process of signalling underlying qualities has the following structure: (1) sender has an underlying quality; (2) sender transmits signal to convey the unobservable quality; (3) receiver notices and interprets a signal; (4) receiver provides feedback to signaller.	Akerlof 1970; Spence 1973; Weiss 1995; Spence 2002; Connelly et al. 2011	Busenitz 2005; Higgins and Gulati 2006
Attention-based View (ABV)	The primary notion of ABV is that decision-makers, given their bounded rationality, have limited ability to respond to a universe of external and internal stimuli surrounding them (Barnett 2008).	ABV is based on three main principles: (1) focus of attention: decision-makers focus their attention on a limited set of issues and answers, and that determines what they do; (2) situated attention: the attention of decision-makers is situated in the firm's procedural and communication channels; (3) structural distribution of attention: the distribution of issues, answers, and decision-makers within the various channels depends on the rules, resources, players and social positions within attention structures.	Ocasio 1997; Barnett 2008	Barreto 2012

Table 3-2: Application of theories

Theoretical Lens	***Real Options Reasoning***	***Signalling Theory***	***Attention-based View***
Rationale for Inclusion	**Empirical relevance** *-content*	**Conceptual reasoning** *-process*	**Theoretical application** *-outcome*
Type of Decision-making	Deliberate *Organisations invest to maximise operating efficiency*	Emergent *Organisational investment is the product of sense-making*	Bounded *Organisational investment is the product of perceptual biases and intuition*
Anticipated Contribution	The study assumes that the funders in the current setting follow the ROR logic to sequence the process of potential value creation. The main focus is to identify the effects of ROR funding allocation outcomes on performance outcomes. The primary expectation is that the presence of the ROR logic in investment decisions will be reflected in high investment yield and firm performance when: (1) initial funding commitment is low (2) discontinuation of funding is low (3) sequencing of funding is low (4) fit of funding decisions is high	Investors use a cue approach to attend to observable signals that would allow them to infer firms' underlying abilities and draw conclusions about given projects' potential performance. A requirement to include specific information in a funding application form indicates that investors consider this information as an important signal of firms' underlying quality. The primary expectation is that the value of a real option will be affected by signals of: (1) legitimacy (2) capabilities (3) project attractiveness (4) efficacy	Routinised review processes imposed by organisations lead to conserved attention and decision-makers can only respond to information that they notice. As such, selective attention can both facilitate and inhibit strategic perception and action. By integrating the concept of situated attention under the ABV, the study suggests that more salient signals received via application forms are stronger than any other visible signals. Hereby, the intention is to examine whether the following mechanisms affect outcomes of investors' decision-making: (1) signal observability (2) signal salience (3) presence of distortion mechanisms

3.2 Real Options Reasoning

Summary of the Main Theoretical Propositions of Real Options Theory

Turgot's writings on the formation and distribution of wealth laid the foundations of capital theory and classical economics (Brewer 1987). The question of what comprises the 'cost of capital' when yields on funds used to acquire assets are uncertain has been addressed by three schools of economic thought: (i) corporate finance is concerned with financing of firms for growth and survival; (ii) managerial economics is concerned with capital budgeting; (iii) and economic theory is concerned with understanding investment behaviour (Modigliani and Miller 1958 p.261).

The classical economic theory valuates investment and financing decisions in terms of their relative utility function, as defined by the ability to maximise expected yield (Modigliani and Miller 1958). Although the utility approach is helpful in understanding the concept of the cost of capital, it overlooks that valuation of the capital budgeting may be affected by pursuit of own goals of decision-makers (Brennan 1995). To mitigate this agency problem, there has been a move towards capital rationing as a way of putting constraints on capital allocations (Brennan 1995). This, in turn, resulted in a broader change in corporate finance described as *"a shift away from attempts to prescribe normative rules for decision makers that would assist them to take decisions that are optimal from the point of view of shareholders and towards attempts to describe more realistically the way that decisions are actually made"* (Brennan 1995 p.17), manifested by the first option pricing model by Black and Scholes (1973).

The primary contrasting assumption of an options approach distinguishing it from conventional investment models is that the process of incremental resource allocation grants the right to firms to pursue investments only if their sequential outcomes are positive (McGrath 1997). Capital budgeting process under the real options view is consistent with the utility maximisation objective, but also allows integrating strategic information in the process of systematic decision-making regarding resource allocation (Kester 1984). Therefore, a real options perspective integrates financial and behavioural theories of decision-making (March 1991; Dixit 1992) and accommodates the role of organisational and managerial factors in exercising and redeploying a firm's portfolio of options under uncertainty (Driouchi and Bennett 2012).

Unlike normative models of investments, real options theory accounts for information asymmetries, path dependence, retrospective sense-making, the value of flexibility, and the role of uncertainty (Bowman and Hurry 1993; Kogut 1991). Real options funding logic is characterised by sequential, irreversible investments made under conditions of uncertainty (Dixit and Pindyck 1994), which has significantly changed the decision process related to capital investment (Dixit and Pindyck

1995). An option creates value by generating future decision rights and by allowing access to a greater variety of opportunities. A such, the real options approach depicts the response of decision-makers to their right to make further investments or defer such investments when the future is not certain (McGrath and Nerkar 2004). Once uncertainty associated with the project is minimised, an investor can use its right to expand the options that are favourable and abandon the remainder (McGrath and Nerkar 2004).

Real Options Theory in Strategic Management Research

In strategic management field, the structure of financial options has been applied to evaluating situations with unforeseeable future outcomes such as joint ventures (Kogut 1991), strategic alliances (Vassolo et al. 2004), corporate restructuring (Hurry 1993), production shifting (Kogut and Kulatilaka 1994a), hi-tech ventures (Hurry et al. 1992), foreign direct investments (Li and Rugman 2007), international market entries (Reuer and Leiblein 2000), minority equity partnerships (Folta and Miller 2002), new technologies (McGrath 1997) and R&D activities (McGrath and Nerkar 2004). Moreover, the real options lens has been applied to studying entrepreneurship (McGrath 1999).

The 'wait and see' setting of real options is well-suited for assessing strategic investments (Adner and Levinthal 2004b), while 'keeping options open' allows firms to expand and enter new markets in the future provided the conditions are favourable (Bowman and Hurry 1993). The term 'real option' is used as a primary point of difference between business and financial literature, indicating that initial investments in strategic assets grant the right to exercise an operating option as opposed to a financial option (Kogut 1991). As such, in contrast to financial economics which uses the options lens to assess investments in terms of their economic value, strategic management literature treats options as resource-investment choices and examines actions preceding as well as performance resulting from such choices (Bowman and Hurry 1993).

In an effort to harmonise the extant literature, McGrath et al. (2004) proposed a taxonomy that distinguishes among four distinct definitions of real options. According to the authors, a real option can be conceptualised as: (i) an element of firm's value leading to strategic growth; (ii) an investment project with an option-like structure; (iii) decisions related to a portfolio of investment projects; and (iv) a heuristic for strategic decision-making (McGrath et al. 2004). Further to that, in management stream of research, real options theory comprises concepts of real options valuation (ROV), real options reasoning (ROR) and real options as capabilities, that can have independent existence of each other or be interrelated in organisational implementation (Driouchi and Bennett 2012).

As such, real options approach can be regarded as a decision-making and valuation tool or as a technique to exploit organisational resources. ROV offers a way to quantitatively assess resource allocation and project management processes through integrating possibilities to wait or partly reverse commitment which optimises decision-making (McGrath 1997; Anderson 2000). ROR, the dominant paradigm in real options theory research, refers to option-based thinking, and strategic mapping and planning processes that involve resource allocation and reconfiguration for the purpose of value creation rather than value maximisation (Driouchi and Bennett 2012). Such form of real options approach reflects intuitive heuristics used by decision-makers, with an element of flexibility being implicitly rooted in the investment and operational process (McGrath and Nerkar 2004). Finally, the third stream of research postulates that real options approach is a mechanism for organisational learning and investment in development of new capabilities to create and capture value (Kogut and Kulatilaka 1994b; 2001). This view builds on theories of dynamic capabilities and organisational inertia by investigating the role of stage-wise reconfiguration of resources in the process of firm's evolution under conditions of uncertainty (Kogut and Kulatilaka 2004).

Critics of the real options approach claim that the real options logic is subject to bounded rationality of decision-makers, making the process ineffective and complicated (Adner and Levinthal 2004b; Adner and Levinthal 2004a). The ROR approach is difficult to implement in practice due to organisational complexities, such as perceptual differences in understanding of the real options concepts and implications by decision-makers, and their behavioural pitfalls (Busby and Pitts 1997; Janney and Dess 2004). Proponents of the real options logic stress that learning by doing is embedded in the staged process, which allows to partly reverse commitment in light of new information and sequentially generate knowledge stocks for future exploitation (McGrath 1997; 1999). The realists recognise the critical role of organisational and behavioural boundaries in extracting value from the ROR approach (Reuer and Tong 2007) and that flexibility of staged commitment offers advantages only when organisations are committed to learning and change (Kogut and Kulatilaka 1994b; 2001).

Structure and Key Concepts of Real Options Reasoning

In management studies, a real option refers to the organisation's ability to mitigate effects of uncertainty through flexibility to sequence, stage and reverse commitment in strategic investment choices (Driouchi and Bennett 2012). Such option structure is deemed suitable for analysing organisational resource-committing decisions (Anderson 2000).

Literature distinguishes between two primary types of options: incremental and flexible (Sharp 1991). Incremental options are mechanisms of executing investments in form of calls and puts, the former exercised to proceed with investments and the latter to reverse the investments (Bowman and Hurry 1993). Flexible options, on the other hand, incur no additional investments and instead utilise and redirect existing investment streams (Sharp 1991), which creates a form of strategic change through striking expansion, contraction or switching options (Bowman and Hurry 1993).

Alternatively, researchers have referred to incremental options as inherent, and to flexible options as proactive, to distinguish between investment decisions that are always available to firms irrespective of the circumstances in the former case versus the ones that require planning and platform building in the latter case (Kogut and Kulatilaka 1994a). However, before any of these options can be exercised, they first need to be recognised from a window of potential, or shadow, options (Bowman and Hurry 1993). The structure of the real options reasoning allows for several forms of flexibility behaviour to respond to new incoming information: to defer, abandon, expand, contract and switch (Trigeorgis 1996; Driouchi and Bennett 2012). Table 3-3 presents a summary of the key option types and the types of behavioural responses that they trigger.

Table 3-3: Summary of option types and corresponding flexibility decisions

Real Option Type	Flexibility Decision[15]	Definition	Rationale
Shadow	Recognise	An option awaiting recognition (Bowman and Hurry 1992).	An option needs to be recognised through assessment of possibilities before being struck. Sequential investments in recognised options grant access to the next option in the chain (Hurry et al. 1992; Bowman and Hurry 1993).
Call	Defer Wait Delay	An option to enter the decision now or in the future (Janey and Dess 2004).	The value of waiting to invest creates extra value (Newton et al. 2004) as deferral of investment for some time does not reduce potential future benefits (Fichman et al. 2005). Instead, it allows to capitalise on upside potential and limit downside risk (Bowman and Hurry 1993). The chances of choosing the winning proposition increase as the time elapses (Fichman et al. 2005).
	Exercise	An option to make the subsequent beneficial decision (Janney and Dess 2004).	The cost of making the subsequent decision is minimised through waiting until new information becomes available (Janney and Dess 2004).
Put	Abandon Discontinue Terminate Withdraw	An option to exit the decision now or in the future (Janey and Dess 2004).	Abandonment allows to reduce losses by reallocating resources from less promising to more promising options (Fichman et al. 2005).
Flexibility	Expand Scale up	An option to make an additional investment outlay (Trigeorgis 1993, 2005).	The scale of allocated resources can be increased to maximise potential benefits under favourable circumstances (Fichman et al. 2005).
	Contract Scale down	An option to reduce planned investment outlays (Trigeorgis 1993, 2005).	The scale of allocated resources can be decreased to minimise potential losses under unfavourable circumstances (Fichman et al. 2005).
	Switch	An option to reallocate investment from the current planned to its best alternative use (Trigeorgis 1993, 2005).	Resources can be redeployed or swapped for alternative options that have higher benefits (Fichman et al. 2005).

Additionally, there are specific parameters that are attributed to implicit employment of options-like decisions in undertaking and managing investments (Driouchi and Bennett 2012). The study by Hurry et al. (1992) found that the venture capital investing firms differ in their strategic decision-making objectives depending on whether they see the investment as a project or an option. Table 3-4 summarises the primary aspects of options-like decision-making.

[15] Multiple terms are used in the literature to refer to the same concepts

Table 3-4: Characteristics of real options investors and their underlying logic

ROR Characteristic	Rationale
Small initial commitment	Initial commitment refers to irreversible sunk cost, which is equal in value to the 'option to defer', or exercise price of the first option (Folta et al. 2006; Jensen and Warren 2001). Therefore, small, manageable amounts of capital limit downside risk (Hurry et al. 1992).
Sequencing	Pursuit of each subsequent stage is contingent on re-evaluation of costs and benefits following exercising of the preceding option. Only options with positive payoffs are pursued. Investors have to make a second investment with a larger amount of capital before return on investment can be realised (Fichman et al. 2005).
Large portfolio size	Exploration of several opportunities simultaneously (Hurry et al. 1992) and extensive investments in opening options, does not discourage to open still more options (McGrath and Nerkar 2004).
High proportion of loss-making ventures	Small possible loss and higher number of potential opportunities in a portfolio result in higher risk-taking behaviour (Hurry et al. 1992).
Long-term and indirect strategic gains	Sequencing allows to hold an option f or an indefinite amount of time until the opportunity to exercise the option arises; moreover, investors are inclined to fund ventures with which they had prior business relations (Hurry et al. 1992).

Empirical Findings of Studies on Real Options Reasoning

Empirical research on real options falls into two categories. On the one hand, statistical and exploratory studies tend to investigate implicit and explicit determinants of real options reasoning, or effects of real options on decision-making and performance (Driouchi and Bennett 2012). Research within this domain is concerned with addressing the impact of uncertainty-flexibility tension on performance and with validating presence of sequential and flexible planning processes in management and investment decision-making (Driouchi and Bennett 2012). In particular, research on the antecedents of real options investments, has presented evidence that interactions of uncertainty and irreversibility, tension between options, portfolio-effects, firm-specific and industry-specific factors have impact on exercising of options and their value (Bulan 2005; Folta and O'Brien 2004; Folta et al. 2006; Vassolo et al. 2004; Tong and Reuer 2006). These findings support the proposition that real options approach of decision-making is used by organisations when evaluating investment options (Aabo and Simkins 2005; Guler 2007a).

On the other hand, research stream investigating consequences of real options reasoning has found impact of multinationality, joint ventures and flexibility on economic and financial performance, risk and growth prospects (Reuer and Leiblein 2000; Tong et al. 2008). The findings indicate that real options decision-making is associated with improved performance and lower downside risk, provided that firm-specific resources and capabilities are accounted for in the analysis (Driouchi and Bennett 2012). It has been recognised that exclusion of intangible assets from analytical models may generate inconsistent results (Pantzalis 2001; Reuer and Tong 2007; Reuer and Leiblein 2000). Such observation calls for more research conducted from a realistic perspective, accounting for the impact of heterogeneity in firms' knowledge capacities on outcomes of real options investments (e.g. Driouchi and Bennett 2011; Tong and Reuer 2006).

The latter suggests that the ambiguity of findings may also be explained by applying more diverse methodological tools to different empirical settings (Driouchi and Bennett 2012). Clear evidence exists of implementation of real options investment procedures in practice (e.g. Busby and Pitts 1997). However, understanding of the mechanisms affecting the link between determinants and outcomes of the real options approach, such as differences in attention and knowledge levels embedded in the decision-making process, is still limited (Barnett 2008; Reuer and Tong 2007).

Real Options Reasoning in Innovation and R&D Contexts

Traditional net present value (NPV) approaches have also been acknowledged inappropriate for valuing R&D and technology projects since they are based on the underlying assumption that the project will advance as intended, irrespective of what future information flow will convey (Dixit and Pindyck 1994; Newton et al. 2004). Real options approach, on the other hand, is a more sophisticated way of dealing with R&D projects as it enables strategic and operational flexibility through a sequence of investments (Newton et al. 2004).

R&D investments have been described as *"backing up the hunch of a research scientist"* (Bowman and Hurry 1993 p.773). The real options lens provides a useful perspective to economically rationalise the intuition of a decision-maker. Technical uncertainty embedded in R&D options, which refers to the likelihood of achieving technical success, can only be resolved through investment (Dixit and Pindyck 1994). By analogy with financial options, high level of uncertainty magnifies potential gains, making an options approach particularly suitable for R&D projects (McGrath 1997).

Breaking down the R&D project into sequential stages enables decision-makers to evaluate the progress before making further investment (Newton et al. 2004). Such iterative and milestone-driven project management approach allows to curtail possible losses through learning and reallocation of resources from losing to winning projects (Eisenhardt and Tabrizi 1995). Technical uncertainty associated with R&D options can be further reduced though deployment of firm-specific intangible assets such as skills, resources and capabilities (McGrath 1997).

Since some assumptions derived from financial options models do no hold in R&D option models, the R&D real options investments are similar to financial only in terms of structure and reasoning, and not in valuation rationale (McGrath 1997). In contrast to a financial option which is valued based on the price of its underlying asset, an R&D option cannot be approximated based on the price of its underlying technology asset because it is not known. Instead, the price of an R&D

option relates to its cost of development and is equivalent to the price to take out the option (McGrath 1997).

Successful completion of the development stage generates a subsequent option to commercialise the technology following additional commitment of capital or to abandon it (McGrath 1997). Finally, the value can be extracted from the option through returns on licensing out or by exploiting the commercialised technology (McGrath 1997). As such, R&D option value comprises three elements: (i) development cost, (ii) commercialisation cost; (iii) value of the underlying claim on the upside cumulative returns from operations (McGrath 1997). The underlying idea is that an R&D option is regarded as worthy of investment if its claim for the upside potential payoff is greater than the cost of development (McGrath and MacMillan 2000).

Prior literature has identified ten applied practices of real R&D options: general R&D planning, planning R&D in stages, evaluating test information, new product development timing, operations, abandonment, risk sharing, market funding, industry strategy and regulation (Paxson 2003). A number of authors applied the real options approach to the staged NPD process. An option gives the right but not the obligation for future decision, which makes it equivalent to an opportunity (Dixit and Pindyck 1995). Therefore, investments in R&D create opportunities for patents and new technologies, and a go or no-go decision during the stage-gate process relates to the option to exercise or abandon the option (Dixit and Pindyck 1995).

Lint and Pennings (2001) used a real-options lens to merge R&D, marketing and financial perspectives in a stage-gate framework, which comprises three stages and grants the decision-makers the flexibility to either proceed to the next stage of the NPD process or to stop it after completion of any stage. Under this framework, (i) idea generation stage refers to the option assessment for R&D portfolio, (ii) research and development stage relates to the option assessment for launch portfolio, and finally (iii) validation stage to the decision to launch (Lint and Pennings 2001).

Similarly, Jensen and Warren (2001) employed a real-option approach for a project lifecycle model that includes a research stage, a development stage and an implementation stage. Successful completion of each stage is associated with a call option to succeed to the next stage, which allows to capture the multi-stage nature of the NPD process and take into account development costs at each stage (Jensen and Warren 2001). As can be seen, a multi-stage nature of R&D activities is similar to a compound option, whereby the value of each ongoing stage is contingent on the potential value of each subsequent stage (Trigeorgis 2005; Chevalier-Roignant et al. 2011). Given the practical relevance of the compound option approach to evaluating R&D opportunities, more research in this domain will help explain critical strategic issues faced in various empirical contexts (Trigeorgis 2005).

Use of Quantitative Methods in Real Options Reasoning Studies

There has been a move towards a more realist approach in quantitative studies building on the ROR logic (e.g. Vassolo et al. 2004). However, application of quantitative modelling in the field of strategic management has been limited in scope (Scherpereel 2008). Accurate model building is constrained by the difficulty to locate the research setting in which real options model assumptions reflect the actual context and to determine the appropriate proxies for discrete inputs used in the options-like process (Bowman and Moskowitz 2001; Miller and Waller 2003). Nevertheless, despite some practical issues related to implementing quantitative real options models, there is increasing support that real options reasoning matches intuition of decision-makers (Scherpereel 2008). This notion is expressed in the paper by McGrath and Nerkar (2004 p.87), which stresses that *"options reasoning is often found to be more consistent with the pattern of choices made by organisations than are other investment alternatives".*

Research applying the ROR logic to positivist-induced principles to investigate antecedents and consequences of the ROR decision-making has only started to develop in the last ten years (e.g. McGrath and Nerkar 2004; Belderbos et al. 2014). Existing quantitative studies on real options have tended to employ secondary data analysis to test the hypotheses pertaining to the decision-making logic under the real options framework (Reuer and Tong 2007). The scholars have acknowledged the difficulty of obtaining micro-level details on real options and their exercising properties in organisational context. There is presently a scarcity of statistical studies that explicitly investigate the "*generalised effect of real options decision-making on performance, or the structural interactions between real options determinants and firm performance outcomes"* (Driouchi and Bennett 2012 p.51). As a result, there has been a growing recognition that quantitative studies will help shed light on different aspects related to processes of exercising options and the bounded rationality of decision-makers in implementing ROR in organisations (Barnett 2008; Reuer and Tong 2007).

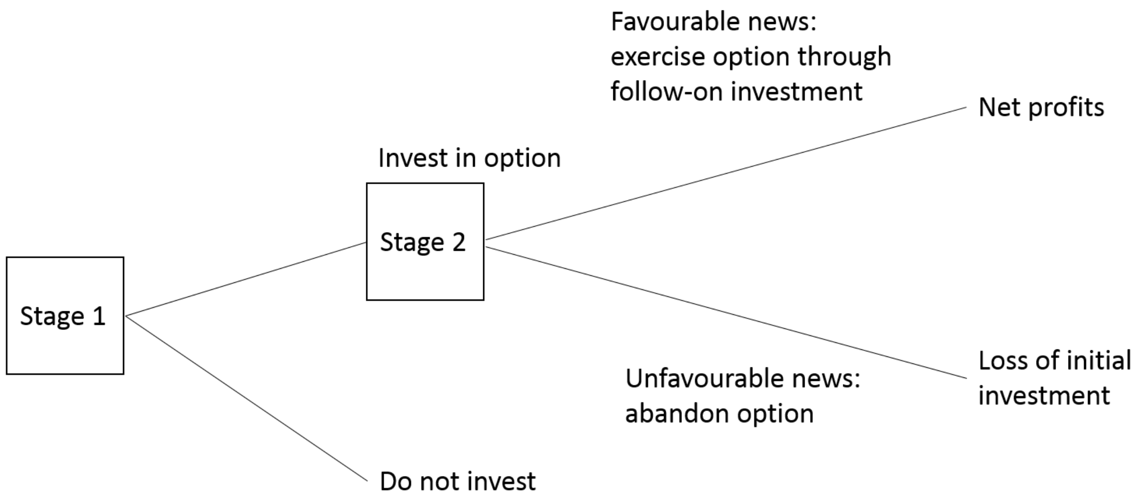
Relevance of Real Options Reasoning to the Current Study

As discussed in the previous section, the literature distinguishes between ten applied practices of real R&D options (Paxson 2003). The present study focuses on general R&D options and their execution in stages, as well as issues related to abandonment and sequencing. Moreover, two conceptualisations of real options from the proposed taxonomy by McGrath et al. (2004) are relevant here. The projects are treated to have an options-like staged structure which refers to the ability to portion financial commitment and delay action until more information comes through. Under this view, it is theorised that a sequence of choices conforms to real options reasoning, and empirical effort is directed at confirming whether the actual choices reflect the theory. Such view also builds upon real options reasoning as a heuristic to refer to the rationally-constrained investment logic that guides decision-making of sequential resource allocation. As such, it reflects a strategic approach to build a portfolio of opportunities and capabilities for the long-term benefit.

Since many, if not all, characteristics of real options investors summarised in Table 3-4 are present, the study hereby proposes that the venture funding programme follows the explicit ROR structure. The structure is expressed in Adner and Levinthal's (2004b) schemata depicted in Figure 3-2 and explains the steps that government funders take to sequence the process of potential value creation.

First, funders invest in a number of Phase I projects (Stage 1). By doing so, the funding federal agency creates a portfolio of options and preserves the right to defer further investments in those options until a major part of uncertainty about their viability has been resolved. Therefore, to minimise the level of perceived uncertainty, investors attend to signals that arise during Phase I or after its completion to approximate the current value of the option. Finally, when Phase I awardees apply for Phase II funding, investors are faced with two types of flexibility decisions: to either exercise or abandon the option (Stage 2). Given the sequential nature of decision processes attributed to real options investments under uncertainty, abandonment, which arises from the decision to withdraw funding from the project, is a vital mechanism for funders to limit downside risk (Bowman and Hurry 1993; Adner and Levinthal 2004b).

Figure 3-2: The structure of real options



Source: Adopted from Adner and Levinthal (2004b p. 75)

Adner and Levinthal (2004b p.75) stress that *"investments with this structure are option-like in that Stage 2 investments are not a necessary consequence of having made an initial Stage 1 investment but, rather, can be conditioned on the realisation of interim information"*. In that respect, the authors emphasise that it is crucial to distinguish ROR from structured and sequential decision-making triggered by sheer path dependency. Although it was later argued by McGrath et al. (2004) that some types of investment projects may benefit from flexibility offered by trial-and-error learning which evolves through incremental path-dependency, evaluation of individual investment projects may be difficult when the underlying propositions of real options theory are relaxed.

In particular, given that in the present setting the investment decision is made by the external funder and not the firm conducting the project, it is important that the decision-makers' economic logic is specified a priori. For the ROR structure depicted in the schemata to be valid empirically, two critical conditions have to hold true: (i) the value of the option should be independent of the investor's behaviour and (ii) the signal of option value should be visible and not manipulated by the investor's actions (Adner and Levinthal 2004b). Both features are present in the current study context—neither can the funding federal agency affect the attractiveness of internal project characteristics, nor influence receivable signals.

Additional critical prerequisite for the validity of the ROR framework is a high level of rigour in the design, planning and management of processes related to real option evaluation. That is, decision-making needs to be carried out in a disciplined way, and heuristics for choices should be specified ex-ante (Adner and Levinthal 2004b). In the absence of clear criteria for determining success or failure, the asymmetry between positive and negative signals complicates the interpretation of option value, and decision-makers may be inclined to use the flexibility of sequential investment to let the option unfold through further learning, exploiting the path-dependent as opposed to the option-like approach (Adner and Levinthal 2004b). Therefore, the scope of potential opportunity and option expiration dates should be defined before the initial investment, so that the technical and market viability can be assessed against the deadline to justify the 'continue' or 'abandon' option. This condition is also met in the study as funding agencies follow explicit evaluation criteria making it possible to justify continuation or discontinuation of projects. Moreover, distinct stages of the government venture capital initiative are clearly demarcated and defined a priori with project and budget start and end dates, as well as application deadlines to proceed from Phase I and Phase II, so options have a definite, exogenous expiration date.

The last indication of the presence of ROR in R&D strategic initiatives worth noting here is manifested by strong orientation towards exploratory research activity (Dixit and Pindyck 1994). Exploratory research is strongly associated with the increased likelihood of substantial scientific advancements that have the potential to open up new options for potential future development (McGrath and Nerkar 2004). Strong orientation towards exploratory research is evident from the mission of the government venture capital programs *"to support scientific excellence and technological innovation"* (e.g. SBIR 2015).

Given the theoretical premises described above, it can be concluded that the ROR framework is deemed appropriate in the current empirical setting. First, the stage-wise process of building a portfolio of opportunities for potential value creation explicitly follows the ROR structure. Second, the underlying option value develops independently of investors' actions. Third, investors follow a priori specified evaluation criteria to assist the decision-making process at clearly demarcated points in time. Finally, potential value embedded in R&D opportunities is derived through the process of exploration.

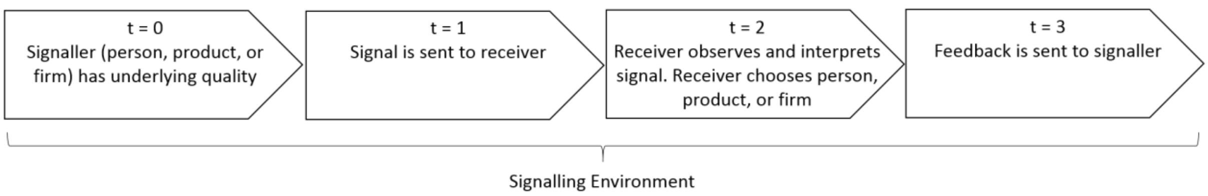
3.3 Signalling Theory

Summary of the Main Theoretical Propositions of Signalling Theory

Individuals make decisions based on available information, but because some information is public and some is private, *"different people know different things"* (Stiglitz 2002 p. 469). In other words, since information exchange is imperfect, it causes information asymmetry. In particular, there are two critical characteristics of information that can get affected under conditions of asymmetry: quality and intent (Stiglitz 2000). Quality-related information asymmetry occurs when one group is only partially aware of the attributes of another group, while intent-related information asymmetry occurs when one group is only partially aware of the behavioural rationale of another group, which causes moral hazard (Connelly et al. 2010).

Signalling theory plays a profound role in explaining how parties resolve information asymmetries about underlying qualities (Connelly et al. 2010). The theory has its roots in financial and economic models (Riley 2001) which are concerned with *"informational aspects of market structure to study the ways in which markets adapt, and the market consequences of informational gaps for market performance"* (Spence 2002 p.435). The key premise behind signalling theory depicted in Figure 3-3 is that senders transmit signals to convey their latent and unobservable abilities to meet a set of receivers' essential and pre-defined requirements; then, receivers notice and decode these signals, which results in responses (Connelly et al. 2011). As such, at the core of signalling models are the signallers who possesses insider information and choose to intentionally transmit it in order to lean the outcome of the outsiders' decision-making process in their favour. On the other hand, the receivers also benefit from information exchange by being able to make a more informed choice. In sum, although both parties may have conflicting interests, the signalling process manifests the potential for strategic gains to the signaller as well as the receiver.

Figure 3-3: Signalling timeline



Source: Adopted from Connelly et al. (2011 p. 44)

Key Concepts of Signalling Theory

Market signals have been analysed in many scientific domains, including economics, finance, marketing, psychology, strategic and human resource management, and applied to many different empirical settings characterised by information asymmetry (Connelly et al. 2010). Advances in research resulted in proliferation of important constructs relevant to the understanding of signalling theory, which are summarised in Table 3-5.

In order for a signal to be efficacious, it has to comprise two attributes—be easily observable and costly (Connelly et al. 2010). In other words, not only the signal has to be visible to the outsider, but also expensive to produce. The notion of costly-signalling theory (Bird and Smith 2005) is an important mechanism to differentiate between sincere and deceptive candidates (Ndofor and Levitas 2004). The underlying logic maintains that the cost of producing the signal is lower for the parties that actually possess the intrinsic quality associated with that signal; that is, the cost of signalling and the unobservable attribute are negatively correlated (Spence 1974). The resultant cost-quality trade-off is known as separation (Spence 2002), which helps to distinguish high quality from low quality signallers. However, if the low quality signaller can afford the cost of producing the false signal without having the underlying ability, it results in dishonesty of the signaller (Durcikova and Gray 2009), or the signal lacking fit. Subsequently, signal fit is described as a statistical relationship between the visible signal and an invisible quality of the signaller, which, together with honesty, forms notion of a credible signal (Zhang and Wiersema 2009). Additionally, there is literature that differentiates between the visibility and strength dimensions of the signal, whereby the latter refers to the perceived importance to the receiver, and presents a third characteristic of an efficacious signal (Ramaswami et al. 2010).

Signals can also be described in terms of their temporal effects and literature tends to differentiate between point and flow signals (DeKinder and Kohli 2008). Certain qualities do not change over time and are perceived as snapshots at a specific point. However, dynamic market environments often require up to date information to reflect recent changes (Davila et al. 2003). In that case, firms can increase signal frequency to minimise information asymmetry (Janney and Folta 2003; Janney and Folta 2006).

Moreover, research evidence exists that efficiency of the signalling process is also affected by the receivers' attention and interpretation (Heil and Robertson 1991), as well as the level of surrounding noise in the environment (Ehrhart and Ziegert 2005). Receivers are unlikely to notice any signals if they are not paying attention to (Gulati and Higgins 2003) or are not proactively scanning (Ilmola and Kuusi 2006) the environment in which the signal may appear. Similarly, signals may receive different levels of importance or get cognitively distorted by the receiver depending on their interpretative framework as well as existing perceptions and preconceptions (Branzei et al. 2004). In the same vein, the signalling environment can introduce the distortions that prohibit effective resolution of information asymmetry (Lester et al. 2006).

Table 3-5: Key signalling theory constructs[16]

Macro Construct	Micro Construct	Definition	Level	Source of Theory
Efficacy	**Observability**	The extent to which the signal is visible, or noticeable to outsiders	Signal	Certo et al. 2001
	Strength	The extent to which the signal is important, or salient, to outsiders	Signal	Ramaswami et al. 2010
	Cost	The extent to which the signal is costly to produce to the signaller	Signal	Bhattacharya and Dittmar 2001
Reliability	**Fit**	The extent to which the signal is correlated with unobservable quality	Signal	Zhang and Wiersema 2009
	Honesty	The extent to which the signaller has the underlying quality associated with the signal	Signaller	Ndofor and Levitas 2004
Temporal Effect	**Point**	The pattern of signals at one point in time, which refers to static attributes, behaviours or states	Signal	DeKinder and Kohli 2008
	Flow	The pattern of signals over time, which refers to changing attributes, behaviours or states	Signal	DeKinder and Kohli 2008
Cognition	**Attention**	The extent to which receivers carefully scan the environment for signals	Receiver	Heil and Robertson 1991; Gulati and Higgins 2003
	Interpretation	The amount of calibration applied by the receiver which distorts signal strength or meaning	Receiver	Branzei et al. 2004; Ehrhart and Ziegert 2005
Noise	**Distortion**	The level of noise present in the signalling environment which reduces signal visibility	Environment	Rynes et al. 1991; Lester et al. 2006

[16] The list is not exhaustive but is rather focused on the constructs that are relevant to the present study

Signalling Theory in the Entrepreneurship Literature

Information asymmetry is especially evident in contexts associated with high uncertainty, such as valuation of small or new ventures. Therefore, signalling theory has gained prominence in entrepreneurship literature (Connelly et al. 2010).

Empirical studies in the entrepreneurship domain have used signalling theory to investigate signalling properties of the structure of the board of directors (Certo 2003; Certo et al. 2001), characteristics of top management teams (Lester et al. 2006) and new venture teams (Busenitz et al. 2005), or involvement of founder and business angels (Elitzur and Gavious 2003; Bruton et al. 2009). Significant amount of literature in the entrepreneurship domain has applied signalling theory in the context of young firms starting-up (Elitzur and Gavious 2003) or undergoing an initial public offering (IPO) (Filatotchev and Bishop 2002; Certo 2003), although studies in the strategic management field have more broadly analysed the effects of signalling patterns by firms (Basdeo et al. 2006), managers (Goranova et al. 2007), directors (Miller and Triana 2009) and CEOs (Zhang and Wiersema 2009). In the field of entrepreneurship, the receivers of intended signals are most likely to be current or future investors, either private, such as VCs and investment bankers (Busenitz et al. 2005; Daily et al. 2005) or public (Cohen and Dean 2005; Jain et al. 2008).

Signalling theory in the management context seeks to explain how economic actors make choices based on limited information (Bergh et al. 2014). The primary proposition of the signalling theory is that firm characteristics, activities and attributes convey information that helps investors form opinions about or increase confidence in firms' inherent qualities (Spence 1973). Signals are used by individuals and organisations to reveal their qualitative differences to affect perceptions of decision-makers within markets about their idiosyncratic value.

Such signals are important mechanisms for young firms to resolve newness and validity bias (Higgins and Gulati 2006). The dearth of objective data on firms' operational and financial performance maximises the chances of adverse selection (Sanders and Boivie 2004). In cases when the widely accepted metrics of firm's quality are unavailable, investors rely on alternative information sources to minimise the chances of adverse selection in the process of filtering and sorting firms. In such situations, visible signals of inherent quality act as credible proxies for absent objective data on firms' performance (Sanders and Boivie 2004). Hence, observable characteristics of firms are treated as implicit points of difference between higher and lower quality firms due to their perceived association with true and pursued, but unobservable characteristics (Weiss 1995).

The extant literature suggests that under conditions of uncertainty markets attend to socio-economic and status factors, which are likely to be easily observable, to sort economic actors and decrease information asymmetry (Sanders and Boivie 2004). Stuart et al. (1999) outlined two broad groups of information that are positively associated with the perceived quality of a young entity by the markets. First, prior accomplishments of nascent ventures signal their latent abilities to achieve success; second, the characteristics of network partners signal reputation of firm's affiliates, which magnifies perception of firm's own value (Stuart et al. 1999). As such, decision-makers attend to signals of social and economic characteristics as underlying drivers of heterogeneity in firms' perceived value.

Likewise, given the myriad of options that investors have to consider at any given point in time, they use a cue approach to simplify the decision-making process. Investors attend to signals that would allow them to draw conclusions about given firms' or projects' potential performance without having to investigate it thoroughly (Su and Rao 2010). Therefore, investors use observable socio-economic and status attributes as alternative information cues and, because of their costliness to imitate, perceive them to be reliable second-tier indicators of quality that help them shape their expectations of the potential value of nascent ventures and their ability to yield returns in the future (DeKinder and Kohli 2008). The stronger the signals of potential value, the more likely investors are to continue funding the venture (Busenitz et al. 2005).

Indicators of Signal Quality

Management studies have attended to institutional, upper echelons, network, and agency theories to identify a number of signals of value. One central theme that combines all these theoretical perspectives is the notion of legitimacy which is an indirect signal of quality. Literature has frequently linked the concept of legitimacy with more symbolical status aspects, such as reputation (Fombrun and Shanley 1990) and prestige (Certo 2003), that can be attributed to boards of directors, TMTs or founders (Lester et al. 2006; Filatotchev and Bishop 2002). Other common proxies for firm's underlying value that have been detected in scholarly work are social ties (Gulati and Higgins 2003) and patents (Warner et al. 2006), among others.

The key premise behind the concept of legitimacy is the social judgement of the actions of an entity as desirable, proper, or appropriate (Suchman 1995 p.574). Thus, to gain acceptance in the market, nascent ventures need to *"create an impression of viability and legitimacy"* (Starr and Macmillan 1990 p.83). Some authors argue that legitimacy is an indispensable yet alterable strategic resource that grants access to other valuable resources and enables new venture growth (Zimmerman and Zeitz 2002; Starr and Macmillan 1990). Moreover, research demonstrates that outsiders associate organisational legitimacy with firm's stock of intangible resources, such as human and social capital, which assure outsiders of the presence of competences and capabilities necessary to improve firm performance (Hillman and Dalziel 2003).

A number of conceptual typologies of legitimacy have been proposed and empirically tested in the extant literature. There is a stream of research that differentiates between three types of legitimacy: (i) socio-political regulatory legitimacy encompasses adherence to rules and standards stipulated by official organisations and can be achieved through acquisition of professional statuses, certifications and accreditations; (ii) socio-political normative legitimacy encompasses adherence to societal values and norms, and can be attained through powerful endorsements from within networks; (iii) cognitive legitimacy refers to mental schemas of understandings and values underpinning behaviours, and is reflected in qualifications and knowledge stocks of the founder or the TMT (Hunt and Aldrich 1996). This typology has been later extended to include industry as a source of legitimacy which refers to collective norms, established operational practices, and the state of technology and know-how (Zimmerman and Zeitz 2002).

The view of legitimacy as a strategic resource was further developed in later works. For example, Tornikoski and Newbert (2007) differentiate between conforming and strategic legitimacy. Conforming legitimacy is a result of a passive adaptation of institutionalised requirements and practices that a credible organisation is expected to meet in a given environment. Strategic legitimacy, on the other hand, is gained through proactive behaviour such as forming and influencing perceptions of different stakeholders in the environment. In essence, however, organisational legitimacy is shaped through a combination of both characteristics and behaviours. To reflect this, the authors developed a taxonomy of legitimacy along four dimensions critical for new venture creation proposed by Gartner (1985)—individual, organisation, environment and process (Tornikoski and Newbert 2007). First, personal and demographic characteristics of an entrepreneur are associated with their skills and abilities and therefore signal trustworthiness. Second, combined ability of the founding and management team is related to organisational capital and industry competence, increasing overall credentials of the firm. Third, industry characteristics such as early stages of life cycle, high growth prospects and low competition signal the potential for new product opportunities and increased anticipated future payoffs. Finally, resource reconfiguration processes and behaviours signal operational capability to produce tangible outputs. In the same vein, Higgins and Gulati (2006) in their study proposed to measure organisational legitimacy in terms of three elements: (i) ability to access resources, (ii) ability to perform key roles, and (iii) ability to attract the reputable endorsements, which young firms can signal though their TMT composition.

A large proportion of literature within the strategic management and entrepreneurship domain has focused on cognitive legitimacy of firm's founder and TMT (e.g. Wang et al. 2014). The main idea is that a qualified founding team can add value to the new venture and hence signal firm's potential to investors. Following this steam of logic, scholars found that entrepreneurs' and managers' characteristics, such as age, education and prior types of experience are widely used by funders to assess the credibility of nascent firms and have a profound effect on outcomes of investment decision-making (Macmillan et al. 1985; Deeds et al. 1997; Deeds et al. 2004; Cohen and Dean 2005; Higgins and Gulati 2006).

Relevance of Signalling Theory to the Current Study

Although real options theory has attracted undivided attention in the strategic management field, scholarly debates on the main attributes of the theory are still widely prevalent, calling for more research on understanding its boundaries to help reach consensus (McGrath et al. 2004).

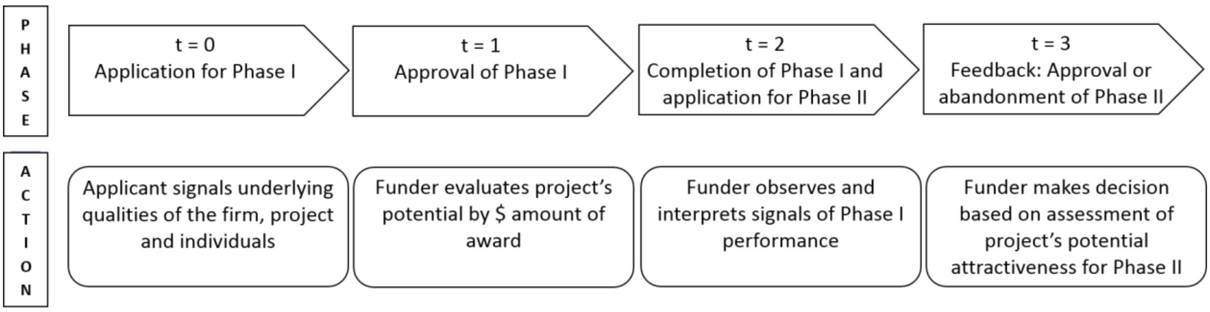
In particular, despite a significant amount of work on normative tenets of real options theory, comprehension of behavioural aspects guiding real options reasoning is still limited. A small number of prior studies focused on the descriptive tenets of the real options theory and found empirical evidence for systematic and unsystematic deviations of decision-makers from prescribed real options logic due to lack of coherent evaluation approaches and imposition of subjective perceptions (Howell and Jaegle 1997; Busby and Pitts 1997; Miller and Shapira 2004).

In comparison to financial options, evaluation of strategic real options is more complicated as decision criteria are less explicit, while 'best practice' planning techniques and cognitive rules to identify and analyse investment opportunities are difficult to develop and implement in practice (Kogut and Kulatilaka 1994b). Additionally, forecasting the value of a new technology or an R&D proposal using universal quantitative methods may not be meaningful because value of an investment is a function of firm-specific assets and capabilities (McGrath and MacMillan 2000). Instead, more accurate evaluation practices of R&D options are based on factors that are proven to be relevant to commercial viability, such as potential market size, state of competition, development and commercialisation costs, scope of the project, firm's resources and capabilities, and industry dynamics (McGrath and MacMillan 2000). The use of explicit and robust assessment criteria simplifies decision-making regarding attractiveness of uncertain R&D projects. Empirical evidence also suggests that investors' valuations of real options tend to be driven by factors pertaining to the macroeconomic environment, the industry and the firm (Tong and Reuer 2006; Alessandri et al. 2007). Although the role of firm-specific core competences is at the heart of strategy literature on real options reasoning, all three levels of factors are important in studying real options due to their possible interactions over time (Alessandri et al. 2007).

The above arguments lead to a conclusion that ex-ante specification of option-like decision criteria stipulated by Adner and Levinthal (2004b) is built upon a set of assumptions which form an option-signal interpretive framework to infer future outcomes. The real options reasoning literature has systematically used the cue approach to explain decision-makers' logic and attended to the signalling theory (e.g. Kogut 1991).

Figure 3-4 demonstrates how signalling occurs in the staged investment process of the government venture capital programme. At t=0, firms include specific information in a funding application form to signal their underlying abilities. In the financing context, the narratives that the borrowers provide to the lenders are necessary mechanisms for information asymmetry resolution and hence facilitate decision-making. Information from bibliographies and application narratives, such as education degrees, age and experience of the TMT, as well as industry certification and professional memberships are clear and efficacious signals of characteristics and behavioural intentions of the borrowers (Zahra and Filatotchev 2004). Therefore, investors evaluate attributes of the applicants based on evidence included in the application narratives, and their perceptions of firms' and projects' potential is reflected in the variation of monetary sizes of awards. At t=2, in addition to already known attributes of applicants, investors also have access to post-Phase I interim information, that can help draw further conclusions about firms' or projects' potential for future payoffs, which results in the decision to continue or discontinue subsequent funding.

Figure 3-4: Empirical map of the signalling environment



Source: Based on Connelly et al. (2011 p.44)

To sum, signalling theory is relevant to the present context both theoretically and empirically. Theoretically, it articulates the behavioural aspects of decision-making under conditions of uncertainty and contributes to the understanding of descriptive aspects of real options reasoning. Empirically, it allows to examine which characteristics of firms, projects and individuals are perceived as signals of quality, or lack thereof, and influence decisions of government venture capitalists to extend or withdraw funding.

3.4 Attention-based View of the Firm

Summary of the Main Theoretical Propositions of Attention-Based View

Early economic models of organisational decision-making were built upon the premises of the rational choice theory, which assumes inherent pursuit of utility maximisation by organisational actors (Simon 1983). However, the practical limitations of this paradigm have been highlighted in behavioural economics and psychology, emerging with the theory of bounded rationality (Simon 1983). Process models of firm's behaviour recognised that *"to explain firm behaviour is to explain how firms distribute and regulate the attention of their decision-makers"* (Ocasio 1997 p.188).

Attentional perspectives of organisational behaviour linking structure and cognition were first introduced by Simon (1947). The later updated and extended version of the theory of bounded rationality, an attention-based view (ABV), explicitly emphasises the role of situated attention of decision-makers and aims to explain differences in firms' attentional processing as evident in heterogeneity of organisation moves (Ocasio 1997).

A model of situated attention and firm behaviour developed by Ocasio (1997 p.192) postulates that decision-makers focus their attention on a limited set of issues and answers which are situated in the firm's procedural and communication channels and structure within these channels determines what decision-makers choose to do. Table 3-6 presents a summary of the main theoretical propositions of Ocasio's model. However, since it is beyond the scope of this study to discuss in detail all theoretical tenets underpinning the ABV, the discussion here will focus on the main ideas and mechanisms relevant to the present context.

Simon (1947 p.220) referred to organisational behaviour as a complex network of attentional processes, in which cognitive procedures of different levels of decision-makers interact and result in a compound action. The environment of decision presents an abundance of stimuli that firms have a limited capacity to process, so they focus their attention on a set of issues which they select through procedural and communication channels (Ocasio 1997). The repertoire of issues and answers is shaped through cognitive sense-making and responsive schemas of decision-makers to react to environmental stimuli and is a result of cultural and institutional processes (Ocasio 1997). Given individuals' limited ability to process several issues simultaneously, evaluation of problems and opportunities utilises organisational memory to draw on standard operating procedures, routines, past actions and learned activities, which enhances selective attention of decision-makers, directing action only towards specific issues (Ocasio 1997).

Literature differentiates between controlled and automatic attentional processing (Shiffrin and Schneider 1977). While controlled processing mode requires high levels of attentional capacity and results in cautiously considered actions, automatic processing is a product of past learning activities and leads to habitual and routinised behaviours. To control attentional processing of individual decision-makers, firms put in place procedural and communication channels (Ocasio 1997). Such channels are made up of concrete activities, interactions, and communications which comprise formal and informal meetings, reports and administrative protocols and play a gate-keeping role of attention allocation on issues that require organisational action.

The availability and saliency of issues and answers in procedural and communication channels (Tversky and Kahneman 1974) are controlled by organisational contexts through three mechanisms: spatially, they restrict the amount of incoming information; temporally, they restrict the timings of decision-making; while procedurally, they restrict the patterns of attention of decision-makers (Stinchcombe 1968). As such, procedural and communication channels facilitate creation of attention structures to direct foci of organisational decision-makers and regulate evaluation, legitimisation and interpretation of issues and answers (March and Olsen 1976).

The firm's rules, resources and social relations structure attention in organisations by generating a set of values, under which issues and answers with greater legitimacy, importance and relevance receive greater levels of attention (Ocasio 1997). While the repertoire of available responses is determined through routines and standardised operations, it is also applied to new issues by drawing analogies with prior responses, situations and activities (March and Olsen 1976). Finally, decision-makers act upon only certain issues which results in a selected number of organisational moves, which subsequently have an effect on the selection of future organisational moves (Ocasio 1997).

Table 3-6: Summary of the main propositions of Ocasio's (1997) model of situated attention and firm behaviour

Theoretical Principles	Level	Description	Components	Mechanisms
Focus of attention	Individual (Simon 1947)	Attentional processes focus the energy and effort on a limited set of issues and answers that enter into consideration, which generates selective attention, facilitating perception and action only towards some specific issues.	Repertoire of issues and answers selected through focused attention	▪ embodiment of issues and answers in firm's activities
Situated attention	Social cognition (Fiske and Taylor 1991)	Decision-makers' focus of attention and resulting actions vary depending on the particular situation they are located in. This principle highlights the role that the link between the organisation and its environmental context plays in shaping individuals' focus of attention and action.	Environment of decision: ▪ economic and financial markets ▪ resources ▪ technology ▪ institutional norms ▪ previous organisation moves	▪ environmental stimuli ▪ cultural and institutional tool kits ▪ environmental embeddedness
			Procedural and communication channels	▪ availability and saliency of issues and answers ▪ interactions of decision-makers
Structural distribution of attention	Organisational (Simon 1947)	Attentional processes of individual and group decision-makers are distributed through organisational functions, with different communications and procedures requiring different foci of attention.	Attention structures	▪ valuation of issues and answers ▪ channelling of decision-making ▪ structuring of interest and identities ▪ structuring of participation ▪ enactment of issues and answers ▪ selection of organisational moves ▪ effects on subsequent moves

Relevance of Attention-Based View to the Current Study

The opponents of real options theory argue that its validity may be abused by investors' bounded rationality leading to flawed decision-making (Driouchi and Bennett 2012). To account for the fact that decision-makers' time and cognitive capacities are constrained (March and Simon 1958; Simon 1947), theoretical tenets of the attention-based view are integrated in the present study.

The primary notion of the attention-based view is that decision-makers, given their bounded rationality, have limited ability to respond to a universe of external and internal stimuli present in their immediate environment (Barnett, 2008). While ROR refers to the logic that investors follow to generate a portfolio of strategic options, an ABV helps understand why investors choose to enact some options but not the others, and brings the investors' evaluation process into the spotlight (Barnett, 2008). Therefore, under the ABV of ROR, to avoid downside losses and capture upside potential of the options in the portfolio (McGrath 1999; Bowman and Hurry 1993), decision-makers must notice and react to signals that they receive. However, given the multitude of projects in the portfolio requiring regular reviews, investors can only attend to selected incoming information to justify their resource allocation decisions and develop reviewing routines to conserve attention (Nelson and Winter 1982). As a result of this, investors' views simplify and narrow (Levinthal and March 1993), which leads to focused attention.

In his paper, Ocasio (1997) noted that the limited capacity for controlled attentional processing highlights the necessity of strategic focus on attention regulation. In an attempt to manage temporal and attentional constraints of decisions-makers, firms develop formal structures and procedures for strategic evaluations (Barnett 2008). The cue approach and decision-making heuristics are known to be widely used procedures by firms practicing ROR. The cue approach centred on the use of heuristics meets the demand of the fast-changing environment in which financial and time resources for complex evaluations are limited, and windows of opportunities are short.

Heuristics are mental algorithms used to find appropriate solutions to real-time problems (Kogut and Kulatilaka 2001). Consisting of two district elements—cognition and rules of search—heuristics have been referred to as procedural search (Simon 1969). However, heuristics have a limited computational ability because the search algorithm cannot generate an optimal solution in a limited timeframe. In reality, the search for optimal answers is often affected by the most recent information (Kogut and Kulatilaka 2001). As such, heuristics are driven by a trade-off between simplicity and accuracy, rather than optimality and because not all opportunities can be measured, such a trade-off is often arbitrary and is based on the best *perceived* decision heuristic (Kogut and Kulatilaka 1994a). Although established project evaluation disciplines cannot prevent decision-makers from mistakenly allocating resources to failing projects (Type I error) or from discontinuing projects that could thrive in the future (Type II error), they help balance the trade-off (Barnett 2008).

Prior literature has attempted to integrate the attention-based view with the signalling theory in the context of investment decision-making. For example, Gulati and Higgins (2003) suggested that investors' attention is affected by contextual factors in the market such as signals of endorsements and partnerships of the potential borrower firm and found support that ties to different external capital providers have different signalling effects under favourable versus unfavourable market conditions. Similarly, studies provided evidence that firm's prior experience with reputable private equity investors (Janney and Folta 2006) or firm's bundling of private equity with research partnerships (Janney and Folta 2003) are perceived as a positive signal by future potential investors, thereby attracting their attention. Prior empirical findings also indicate that evaluation of strategic investment options is driven by decision-makers' intuition (Bowman and Hurry 1993; Slater et al. 1998).

Following the logic of existing scholarly work, in the present study, attention-based view is applied to interpretation of received signals. By integrating the concept of situated attention under the ABV, the aim is to explain how attributes of received signals help focus attention of boundedly rational decision-makers and affect their ability to notice, encode and transform signals into a limited set of actions which results in the portfolio of real options (Ocasio, 1997; Barnett, 2008).

The view adopted here is that attention of investors is narrowed through the combination of disciplined evaluation protocols and decision-making heuristics, which represent Ocasio's (1997) structural and cognitive processes, respectively. As such, structural processes will control the availability and saliency of information to decision-makers at any given point in time, while cognitive processes will shape their rules of thumb for making judgements and choices. Therefore, formal evaluation practices encourage decision-makers to use heuristics in order to focus their attention and act upon a set of specific issues. However, despite perceived strategic benefits of sustained focusing of attention and effort, unless the procedural and communication channels are designed so that attention of decision-makers is concentrated on appropriate issues and answers, selective attention may actually inhibit decision-making optimality, potentially leading to bias (Ocasio 1997).

3.5 Complementarity of Theoretical Perspectives to the Current Study

Since the seminal work of Burrell and Morgan (1979), a significant stream of research has been directed at explaining organisation theories under the notion of paradigms—scholarly assumptions, practices and agreements. After significant effort has been made to outline the processes of theory building from different paradigms, there has been a call for metatriangulation—a strategy of applying diverse paradigms to gain in-depth insights (Gioia and Pitre 1990), which resulted in a proliferation of multiparadigm studies. Multiparadigm inquiry has been noted to offer immense potential for employing a combination of heuristics engrained in varied philosophical stances for theory-building, aiding in understanding of complex organisational phenomena (Lewis and Grimes 1999). Metatriangulation is especially useful for examining the most disputable realms of organisation theory—by inflicting a unified framework built upon contrasting paradigm lenses, it can help enrich ongoing debates and clarify ambiguous findings (Lewis and Grimes 1999).

As has been expressed by Cannella (2004 p.73), a series of theoretical papers and dialogues on ROR emerged in the Academy of Management Review 2004 issue, resulted in *"a set of truly diverse views about real options and their use in strategic decision making",* that are expected to *"do much to spur the development of both empirical and theoretical work on real options".* To add to the ongoing debate in the ROR field, the present work attempts to implement the multiparadigm approach to investigate the studied phenomena by empirically applying divergent theoretical lenses to examine insights derived from a multiparadigm review of extant scholarly work (Lewis and Grimes 1999). Such approach is expected to contribute to the body of literature by acknowledging the primary premises and limitations of existing theories in order to compare and contrast them with the findings gained from a new empirical setting. An end goal is to understand theoretical confrontations and disparate findings through a novel combination of paradigms. In particular, through a sequence of empirical studies, the present research project intends to link lenses provided by diverse paradigms in a complementary fashion in an effort to grasp the organisation phenomena.

Organisational research integrating financial and behavioural theories is scarce, and little progress has been made towards understanding decision-making processes underpinning innovation investment outcomes (McGrath and Nerkar 2004). The options approach makes an important contribution to the strategic management literature by incorporating four significant theoretical streams in a cohesive framework, proposed by Bowman and Hurry (1993). On the one hand, resource allocation and strategic positioning are related to financial content-oriented frameworks; on the other hand, sense-making and organisational learning are reflected in behavioural process-oriented frameworks (Bowman and Hurry 1993). Two empirically and conceptually relevant theoretical themes have been adopted from Bowman and Hurry’s framework in the present study; namely, resource allocation and sense-making and they focus on explaining the aspects of organisational processes related to the present. Strategic positioning and learning theories related to future-oriented processes were outside of the scope of the study.

Resource allocation is concerned with efficient utilisation of practices aimed at output maximisation to achieve organisational goals and objectives (Bowman and Hurry 1993), whereas sense-making is a naturally occurring form of decision-making directed to inform strategic action (Gioia and Chittipeddi 1991). Sense-making is a resulting product of decision-makers’ interpretation, intuition and cognition which are underpinned by experiences and the system of values and beliefs (Miller 1993). As such, boundedly rational decision-making heuristics that play a profound role in the functioning of organisations (Simon 1991), can undermine the optimality of efficiency-driven resource allocation. Hence, normative financial models that are grounded in notions of efficiency and rationality have a limited ability to explain organisational phenomena (Dixit 1992). Real options lens offers a means to merge the more prescriptive economic logic of financial models with decision-making actuality of behavioural perspectives.

The study builds on extant theoretical and empirical literature to detect investment patterns consistent with ROR (e.g. Hurry et al. 1992; McGrath and Nerkar 2004) and then investigates whether these patterns are also evident in the context of government venture funding. The present research project extends this growing body of work by testing the propositions of ROR in the context of government venture funding. The findings of such inquiry will help to find out whether ROR has to contribute to investment theory in the field of government venture funding.

3.6 Concluding Remarks

This chapter presented an overview of conceptual underpinnings guiding the current research project. The study draws upon the real options reasoning perspective as a dominant theoretical lens, and uses signalling theory and attention-based view to complement understanding of the ROR. First, the study assumes that investors in the present empirical setting follow the explicit ROR structure to sequence the process of potential value creation. Then, to investigate whether the actual investment behaviour is consistent with the theoretically predicted with regards to exercising options, the study utilises signalling theory to understand the evaluation process that investors go through. Finally, understanding of behavioural aspects guiding allocation of funding is enhanced by incorporating ideas prescribed by the attention-based view of the firm.

Chapter 4 - Conceptual Framework and Research Hypotheses

4.1 Introduction

To reflect the objectives pursued in the present study, theoretical developments comprise three parts. Part I is designed to test the propositions of real options reasoning in the context of government venture funding by analysing the consequences of resource allocation decisions. Part II is intended to examine the tenets of signalling theory and attention-based view in the context of government venture funding by investigating the antecedents of funding decisions. Part III is aimed to assess the complementarities of ROR and signalling theories in predicting anticipated performance effects. As such, theoretical foci presented here relate to two different types of risk inherent in all investment projects–strategic and tactical (Chatterjee et al. 1999). As Chatterjee et al. (1999) noted, strategic risks concern market imperfections related to making resource allocations without understanding their potential to enhance performance outcomes, while tactical risks are driven by firm-specific uncertainties associated with information asymmetry.

In line with the theoretical directions outlined above, the section comprises three parts. First, each part presents relevant theoretical constructs and their conceptualisations derived from extant literature. Then, these constructs are linked to the original research questions, resulting in a set of emerged research hypotheses which are discussed in light of adopted theoretical lenses. Finally, configurations of relationships are depicted in corresponding conceptual models.

4.2 Part I: Analysis of Consequences of Government Venture Funding from the Real Options Reasoning Perspective

The primary research question posed in this part is: 'Does an additional unit of government investment at time *t* lead to a better stream of social value from the private sector at time *t+1*?'. More specifically, the same question can be formulated as 'What effect do different outcomes of government venture funding decision-making have on long-term performance?". To address this question, the first step is to theoretically conceptualise possible outcomes of government venture funding from the ROR perspective. The next step is to understand what effects these financing decisions might have on differences in firms' performance.

The stagewise nature of the real options approach, which combines strict screening and filtering criteria in early financing rounds in order to justify subsequent larger resource commitments, fits well with the corporate processes of resource allocation (Adner 2007). In reality, however, there often exists a discrepancy between the prescribed allocation logic and practised reallocation actuality (McGrath and Nerkar 2004). Technically, venture capital setting, with its structure of explicitly demarcated financing rounds, should present the most disciplined execution of real options reasoning logic in practice (Guler 2007a; Guler 2007b). Neutral venture capitalists have a stringent screening discipline and an incentive to terminate financing those externally sourced projects which do not promise expected returns on investment, lowering the level of potential escalation of commitment of project champions (Adner 2007). In the real world scenario, though, the strength of political and social ties between project champions and project funders in the venture capital industry might lead to the rational escalation of commitment in light of sunk capital and jeopardise the disciplined selection and funding allocation mechanisms required by ROR (Guler 2007b). What remains unclear, then, is how closely ideas upon which ROR is predicated reflect the organisational reality. Additionally, current evidence of whether following ROR investment logic leads to improvements in performance remains scant (Krychowski and Quelin 2010) and inconclusive (Li et al. 2007), with findings of scholarly work either indicating a positive association (Levitas and Chi 2010) or no association at all (Reuer and Leiblein 2000).

To explore these gaps, the objectives of Part I are twofold. The first objective is to find out whether explicit real options structure of the government venture capital programme is also manifested in explicit or implicit real options logic. Then, the focus is to test whether propositions of ROR reflected in the investment pattern of the government venture funding scheme have an effect on anticipated long-term performance.

Relationship between Resource Allocation Outcomes and Long-term Performance

The essence of real options reasoning is expressed in its proposed approach for informing resource allocation decisions in organisations, which is built on a number of fundamental assumptions intended to guide the logics of such processes (Adner 2007). These assumptions concern two types of decisions—initial resource allocation and subsequent resource reallocation, and the correspondence of these decisions distinguishes real options decision-making from sequential decision-making (Adner and Levinthal 2004b; Adner and Levinthal 2004a; Adner 2007). Therefore, to differentiate between a coherent and disciplined decision-making prescribed by real options reasoning and a path-dependent decision-making under other sequential approaches, it is important to disentangle distinct elements comprising resource allocation processes (Adner 2007; Klingebiel and Adner 2015). From the arguments described in the previous chapter, constructs relevant to a strategic theory of investment incorporating ROR were identified as initial commitment, discontinuation and sequencing. Literature indicates that real options approach matches these elements in a way that allows to distinguish it from other resource allocation regimes (Klingebiel and Adner 2015).

One of the primary assumptions is that funding decisions undertaken in line with the ROR approach, that is when investment behaviour is marked by a structured and sequential pattern, lead to improvements in corporate performance (Kumar 2005). Investors allocate financial resources to projects they expect to yield returns above sunk costs (Dixit 1992). Bowman and Hurry (1993) described efficient resource allocation as a function of instantaneous cost-benefit judgement and option value, with performance being its by-product arising as a result of lagged interaction with the environment. Investments placed in time *t-1* through their ongoing interaction with the environment create an opportunity in time *t*, which may or may not yield growth in time *t+1* (Bowman and Hurry 1993 p.775). Hence, initial investments exposed to potential interactions with the environment are equivalent to the exploration of opportunities (Bowman and Hurry 1993), while subsequent exercising of options is equivalent to the exploitation of opportunities (Luehrman 1998a). By extension, the entire chain of explore-exploit options stimulates learning from prior investments, building a stock of unique resources and capabilities, which can be leveraged in novel domains, leading to performance advantages.

The classical theory of investment postulates that rational decision-making follows two equally important criteria: profit maximisation and market value maximisation (Modigliani and Miller 1958). In other words, an option is worth acquiring if it will increase the net profit of the owners of the firm and/or the value of the owners of the option; that is, if its expected rate of return, or yield, exceeds the costs of acquisition. Accordingly, the profit and value maximisation criteria of the investment model tend to evolve into utility maximisation function and what the option adds can be assessed in terms of the stream of value it generates (Modigliani and Miller 1958). Under this approach, any investment project must raise the private and public value of the firm's performance (Modigliani and Miller 1958). Following this line of reasoning, real options are expected to offer performance advantages to both project initiators and project funders, whereby the former can enjoy effects of iterative learning and incremental capability building, while the latter can benefit from improved resource allocation decisions offered by the flexibility of ROR. Consequently, outcomes of investment were conceptualised from two perspectives—investors' and firms'.

The primary objectives pursued by the government investment programmes are to increase commercialisation, encourage entrepreneurship and stimulate innovation. To reflect this, anticipated performance outcomes of real options investments were conceptualised along three dimensions as post-funding sales performance, employment creation and innovation activity. Accordingly, yield on investment denotes the funders' desired outcomes, and absolute performance denotes firms' desired outcomes.

To sum, in line with previous literature (Klingebiel and Adner 2015), the study proposes that distinct elements of real options reasoning—initial funding commitment, funding continuation, funding sequencing, and fit of funding decisions—might have differential effects on investment yield and long-term firm performance. The hypothesised links between different elements of ROR and anticipated performance outcomes are discussed in detail below.

Resource Allocation to an Individual Option

Initial Commitment

The initial investment signifies a strategic decision because it creates an opportunity for subsequent moves (Luehrman 1998a). By rationing the investment fund into smaller grants, the options approach allows to pursue a wider range of opportunities concurrently with the same amount resources, learn quicker about the promising projects, and rule out the rest (McGrath and Nerkar 2004). In this respect, initial investments grant the right to pursue opportunities in the future, while keeping initial capital commitments low minimises downside risk, making abandonment of options more viable (Kogut 1991). As such, initially small irreversible sunk investments are equivalent to opportunity costs of waiting (Folta et al. 2006). As pointed by Barnett (2008 p.619), the primary idea behind keeping initial investments low is "*to establish toeholds - not make large footprints*" until the uncertainty is reduced.

Hence, stagewise exploration of multiple options via small rather than large investments allows managing the risks associated with uncertainty, before embarking on full-scale commitments at a later point in time (Bowman and Hurry 1993). When the portion of uncertainty about the option is reduced through a trial investment, the opportunity can be further exploited with a larger investment. Given that potential loss-making from investments is limited to their sunk costs a priori, smaller initial financial instalments activate learning, experimentation and development of capabilities necessary to explore the potential opportunity (Hurry et al. 1992).

As Bowman and Hurry (1993) argued, real options logic adds value to the investment process when initial investments are low and are followed by exercising of options via larger resource commitments. Such chains of 'learning' enabled through 'incremental commitment' options are especially effective in the contexts of novel technological areas, new ventures and new markets. Therefore, the expectation is that keeping initial commitments low will have a positive effect on performance. For firms, performance outcomes are likely to be enhanced through learning and capability building facilitated by option-like explorations of multiple potential avenues, while funders are likely to improve returns on investment by allowing firms to grow and develop at a small cost. Conversely, upward deviations of initial commitments will be negatively associated with anticipated performance.

H1-1: The magnitude of initial funding commitment has a negative effect on investment yield—(a) sales yield, (b) employment yield, (c) innovation yield, and firm performance—(d) sales performance, (e) employment performance, (f) innovation performance.

Discontinuation

As was described in the earlier chapter, the call options embedded in investment projects grant flexibility for the exercise decision, whereas the put options grant flexibility for the abandonment decision (Trigeorgis 1996). Abandonment, also referred to as withdrawal or discontinuation, is another element pertaining to real options investments. Abandonment allows discontinuing a stream of investments in response to new unfavourable information (Adner and Levinthal 2004b) and convert an active project into an idle one (Dixit 1989). Consequently, it has been defined as *"the indirect result of the decision to deny resource allocations."* (Barnett 2008 p.621).

To gain from flexibility offered by ROR, options not only have to be effectively selected from a pool of opportunities and exercised, but also abandoned in a timely fashion when they go down in value (Barnett 2008). When exploration of technological opportunities to determine their future potential is carried out over the extended period of time, it reduces organisational focus and eventually the cumulative performance (Miller and Arikan 2004). Hence, the decision to defer exercising the option incrementally decreases its value over time (Trigeorgis 1996).

Investment logic dictates that to increase future potential advantages from financing activities, losses should be incurred in the short-term (Kogut and Kulatilaka 1994b). However, this logic goes counter to investments in R&D projects and new ventures, which tend to require infusions of capital over a prolonged period of time before they can generate any paybacks in the future. Withdrawal of funding offers flexibility to restrict investment costs to irreversible sunk capital allocated to an R&D project (McGrath 1997). It also creates pressure for investors to strike a balance in a portfolio of explore-exploit options, and to make rational decisions regarding the conclusion of exploration of existing R&D projects and reallocation of resources to other options (McGrath and Nerkar 2004). Isolated projects are easier to discontinue, which indicates that abandonment decision is concerned with balancing a trade-off between the ease of withdrawal and the potential for future value creation (Adner 2007). As was pointed out by Adner and Levinthal (2004b), lack of explicit rationale for justifying abandonment decisions challenges the ability of organisations to benefit from the sequential option-like investment structure. Since abandonment refers to the decision to discontinue allocation of resources to an unpromising option, without a structured and regular review discipline, it would not be possible to determine which options no longer merit further flow of resources (Barnett 2008).

The above arguments indicate that discontinuation is a challenging decision to make due to the difficulty of strategic refocusing in light of sunk costs associated with initial information processing, inertial tendencies induced by rigid organisational routines, and competing pressures of balancing escalation and underinvestment (Ghemawat and Costa 1993; Coff and Laverty 2001). However, the following conjecture is built upon the reasoning that continued investment in opened R&D options can increase their value through the accumulation of relevant knowledge and path-dependent learning (Nelson and Winter 1982). Conversely, discontinuation of investment in opened R&D options ceases the knowledge accumulation process which may conclude the development of the project (Trigeorgis 1996)[17]. In line with this logic is the expectation that discontinuation of an individual project will have a detrimental effect on performance because it might bring the firm's chain of learning to an end, subsequently reducing potential return on investment.

H1-2: Funding discontinuation has a negative effect on investment yield–(a) sales yield, (b) employment yield, (c) innovation yield, and firm performance–(d) sales performance, (e) employment performance, (f) innovation performance.

Fit of Funding Decisions

Correspondence of decisions concerning the initial allocation of resources and subsequent reallocation of resources is what implicitly differentiates ROR logic from other regimes (Adner 2007). The promise offered by ROR to enhance performance is contingent upon the match between early-stage and late-stage decisions (Klingebiel and Adner 2015).

As suggested by Adner (2007), organisations demonstrate adherence to real options logic when initial resource allocation entails low financial commitment and is followed by subsequently disciplined exclusion of projects from a portfolio; or, when initial resource allocation entails high financial commitment and is followed by subsequent exploitation of projects in a portfolio. As such, the discontinuation decision is informed by the magnitude of initial funding allocation, making it more

[17] By analogy with private VC, government VC finances a number of projects in every single round, creating a rolling portfolio of options (Cumming 2006). The value of an individual option is assessed in relation to other options in the portfolio (McGrath and Nerkar 2004). Therefore, exercising the abandonment option through discontinuation of funding does not necessarily signify an absolute unattractiveness of the option, but instead implies its relative unattractiveness given other options in the portfolio. Consequently, discontinuation of funding by itself may not lead to the permanent termination of the project and is a distinct outcome from a natural exit through the IPO (Brander et al. 2002; Gompers and Lerner 2000) or bankruptcy (Gimeno et al. 1997). Instead, the entrepreneur may choose to proceed with the project by accessing capital elsewhere, such as through private VC (Li and Chi 2013). Due to data constraints, it was outside the scope of the study to account for such potential behaviour of entrepreneurs in the present setting.

feasible to discontinue low-cost options, and to continue with high-cost options. In line with the conceptualisation adopted by Klingebiel and Adner (2015), such pattern of options matching is referred to as fit of funding decisions and is expected to have a positive effect on anticipated performance outcomes.

H1-3: Fit of funding decisions, i.e. low initial funding commitment and discontinuation or high initial commitment and continuation, has a positive effect on investment yield—(a) sales yield, (b) employment yield, (c) innovation yield, and firm performance— (d) sales performance, (e) employment performance, (f) innovation performance.

Resource Allocation to a Portfolio of Options

In assessing the effect of ROR on performance, it is important to differentiate between the *possible* and *probable* application of real options logic to strategic decision making (Adner 2007). The debate on the applicability of ROR to strategy concerns the *consistency* between the prescribed approach and organisational reality (Adner and Levinthal 2004b). Hence, to extend the previous conjecture, the expectation is that correspondence of resource allocation decisions under ROR will have a stronger effect at the portfolio level.

H1-4: The performance effect of fit of funding decisions is greater at the at the cumulated portfolio level than at the individual option level.

Sequencing

Strategic execution of projects involves a sequence of important decisions, some of which are taken instantly, while others are put on hold until time resolves a major part of associated uncertainty (Luehrman 1998b). Sequencing plays a critical role in breaking down the project development challenge into more milestone-oriented, iterative and manageable stages (McGrath 1997). Additionally, sequential development allows reducing uncertainty early on through learning and experimentation, without requiring financial commitments at later stages, supporting resource redirection regimes implemented in the form of discontinuation of less promising projects.

Sequencing makes option-like investments attractive because unlike financial commitment made for early stages of development, commitment for later stages of development can be reversed, making costs incurred in the initial resolution of technical uncertainty more controllable and plausible (McGrath 1997). Subsequently, sequencing of financial resources enables greater flexibility to cope with the unfolding project development process, stimulating iterative learning and efficiency, allowing to respond to emerging information with a timely discontinuation of projects and reallocation of scarce resources to more promising alternatives (Bowman and Hurry 1993). Evidence supports the notion that sequentiality offered by the option-like approach enhances capability building and evolutionary learning (Chang 1995; Chang and Rosenzweig 1998; McGrath and Nerkar 2004). Sequencing wins venture capitalists time to obtain and assess new information, which significantly minimises investment risks (Sanders and Boivie 2004).

The primary idea behind real options is that if low-probability projects can be discontinued at minimal costs, the value of remaining projects in the portfolio increases (Gavetti and Levinthal 2000). Hence, the larger the number of early stage projects, the more technical uncertainty can be resolved sooner, enhancing strategic value of option-like investments. Sequential resource allocation helps firms in innovation-driven industries to position their R&D portfolios in line with emerging market demands, facilitating commercialisation of successful new products (Klingebiel and Adner 2015). The intuition hereby is that propensity to sequence too many projects in the portfolio will erode the value of flexibility offered by the ROR approach. In other words, the more projects will be allocated late-stage funding, the lower will be the effect of sequencing on anticipated performance.

H1-5: For firms with prior awards, high rate of funding sequencing has a negative effect on investment yield—(a) sales yield, (b) employment yield, (c) innovation yield, and firm performance—(d) sales performance, (e) employment performance, (f) innovation performance.

Boundary Conditions: Portfolio Effects

The flexibility inherent to real options decision-making is more valuable in relation to a collection of options rather than individual options (Trigeorgis 1993). Scholars refer to a number of individual investment projects as a portfolio of real options (Bowman and Hurry 1993; Luehrman 1998b). If options have comparable properties such as expiration date, price and cost, keeping options in a bundle has a strategic value because the development of options increases economies of scope due to their complementarity (Bowman and Hurry 1993). Otherwise, individual options offer a greater strategic flexibility to increase upside benefits and decrease downside risks when kept separately and independent of each other.

The case when the portfolio is worth less than the sum of its individual options has been coined non-additivity (Trigeorgis 1993), suboptimality (McGrath 1997), or subadditivity (Vassolo et al. 2004). Belderbos et al. (2014 p.90) expressed subadditivity of options A and B in a portfolio as $V(A, B)<V(A)+V(B)$, where $V(A, B)$ refers to the value of the entire portfolio, while $V(A)$ and $V(B)$ refer to the value of the two individual options. Extant research pointed that multiple options may be subject of subadditivity due to their interactions effects causing overlaps in investments, driving down the overall value of the portfolio (Trigeorgis 1993). Therefore, the marginal value of every newly opened

option declines the larger is the size of an existing portfolio of options, indicating that adding up values of individual options will result in overestimation of the value of the portfolio (Trigeorgis 1993).

Existing literature differentiates between two conceptualisations of subadditivity: one stream of research focuses on the correlations between options (Vassolo et al. 2004; Belderbos et al. 2014), while another refers to the number of options in the portfolio (McGrath and Nerkar 2004). The present study follows intuition of the latter group of researchers and expects that because R&D options may interact in a subadditive manner requiring a greater stock of resources, increasing the number of investments granted to the same firms will decrease the expected benefit of such investments and the value of the entire portfolio.

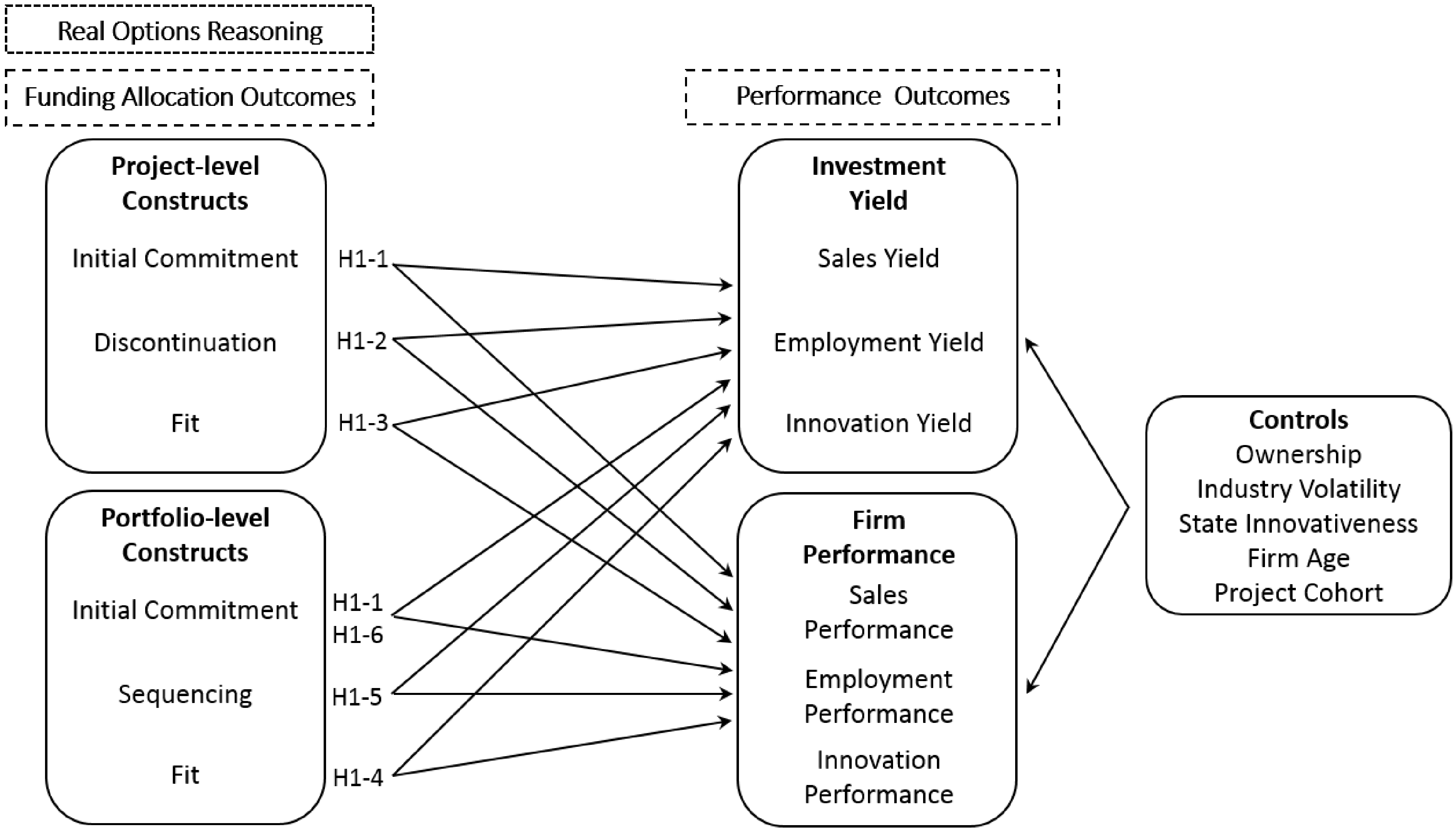
To investigate portfolio effects, the sample is split into two clusters indicating whether or not firms had awards prior to receiving the focal award. The objective of such inquiry is to test the expectation of portfolio subadditivity.

H1-6: An opening of a new individual project has a positive effect on investment yield–(a) sales yield, (b) employment yield, (c) innovation yield, and firm performance–(d) sales performance, (e) employment performance, (f) innovation performance of firms with no prior awards, but an addition of a new individual project to the portfolio of firms with prior awards has no effect.

Part I Conceptual Model

The following conceptual model (Figure 4-1) depicts a set of hypotheses consistent with the expectations that the presence of ROR in investment decisions will be reflected in a propensity to keep initial commitment and sequencing low to minimise downside risks, and to continue projects with high initial commitment and discontinue projects with low initial commitment.

Figure 4-1: Conceptual model I



4.3 Part II: Analysis of Antecedents of Government Venture Funding from Signalling Perspective and Attention-based View

The principal research question this part aims to address is: 'Which signals affect funders' decisions to determine the magnitude of initial commitment and are associated with increased likelihood of subsequent funding discontinuation?'. Additionally, the intention is to examine 'Which attributes or categories of signals receive higher levels of funders' attention and, therefore, have a stronger effect on funding allocation decisions?".

To articulate these inquiries into the filtering process of government decision-makers, the initial stage of conceptual model building is focused on understanding the selection criteria that government venture funders use. Once established, these criteria are then matched with theoretical constructs derived from existing literature. Next, anticipated effects of selection criteria on funding allocation decisions are expressed in a set of research hypotheses testing propositions of signalling theory and attention-based view in the context of government venture funding.

Table 4-1 shows a list of scored review criteria used by government venture capital decision-makers when assessing new applications for funding and their corresponding theoretical counterparts. Signalling constructs relevant to investment decision-making and conceptual indicators making up these constructs were drawn from theoretical arguments discussed in the previous chapter and the review of the extant empirical literature. In line with entrepreneurship research, the focus is placed on legitimacy and capabilities pertaining to the manager and the principal investigator, project attributes and efficacy.

The logic for selecting these constructs is that legitimacy and capabilities are relevant to the intangible assets necessary to proceed in innovation activity, project attributes are relevant to the individual R&D proposition, while efficacy is relevant to the activities of the firm as a whole as well as the viability of the R&D option to reach the commercialisation stage. Therefore, selected signalling constructs represent three levels of factors relevant to analysing the nascent firms' potential to develop a real R&D option. Although selected constructs are proxies, it is believed that they reflect the underlying logic of the review criteria used by investors.

Table 4-1: Matching of scored review criteria with theoretical constructs and conceptual indicators

Scored Review Criteria	Theoretical Construct as Signal Category	Conceptual Indicators
Overall impact on the research field	Existing portfolio characteristics (i.e. history of obtaining funding)	Initial commitment Sequencing Fit
Project significance	Project appeal characteristics	Project programme type
Commercial potential	Project appeal characteristics	Project scope
Suitability of TMT in terms of experience, expertise and record of accomplishments	Role legitimacy	Executive's functional role Organisational tenure Technical experience Entrepreneurial experience
	Resource legitimacy	Elite education Advanced technical education Advanced business education Academic seniority
	Intellectual legitimacy	Inventive capacity Academic competence Abstract readability
	Capabilities	R&D capability Intellectual capability Managerial capability
Novelty & innovativeness of project for research and/or practice	Efficacy	Post-funding innovation activity
Strategic approach to accomplish aims of the project	Efficacy	Post-funding project duration
Conducive research and scientific environment	Network ties & social capital Innovative environment	Academic affiliations State innovativeness

Effect of Attention-Regulating Signal Attributes and Categories on Funding Allocation Decisions

As was noted by Kogut (1991), prior research on cue processing has been predominantly directed at understanding biases involved in information interpretation rather than information selection. However, empirical evidence showed that decision-making efficiency may be weakened due to biases in information selection, in particular triggered by salience and availability of information (Kogut 1991). Such findings imply that investors' decisions are cued by more observable, more salient and more relevant signals.

Observability, Salience and Relevance

The primary notion behind an ABV is that *"focused attention both facilitates perception and action towards those issues and activities that get noticed, and inhibits perception and action towards those that do not"* (Ocasio 1997 p.190). In other words, decision makers only respond to information which is visible to them within their attention domain.

Boundedly rational decision-makers within organisations can only attend to a portion of information cues that they receive (Cohen et al. 1972). An ABV articulates how organisational structures impact decision-makers' ability to respond to a selected number of stimuli. Attentional structures, which are regulated by adhering to organisational goals, stimulate actions of decision-makers towards more salient cues and divert their attention from less salient cues (Barnett 2008). Sociologists note that perceptual salience increases attention towards information which is more relevant to the decision-making process (Fiske and Taylor 1991). For instance, firm's recent experiences and actions are more salient due to their temporal relevance and decrease the receptiveness of risks associated with option-like decision-making (Barnett 2008). Therefore, investors may develop ideas about the importance of specific signals and apply higher weights to such signals during the evaluation process (Ehrhart and Ziegert 2005).

Following this line of reasoning, the hypotheses outlined in subsequent sections express the expectation that signals which are perceived by investors as more observable, more salient and more relevant will have stronger attention-regulating effects and will bear greater weights on funding allocation decisions.

Relationship between Top Management Team Legitimacy and Funding Allocation Decisions

Success of new ventures is often a result of collective effort of a team of individual entrepreneurs whose heterogeneous experiences and abilities contribute to the achievement of organisational goals (Unger et al. 2011). Hence, complementarity and diversity of skills of team members lead to superior venture performance (Ensley et al. 2002). TMTs of small firms have to take diverse functional roles, for which they need to possess both technology- and business-specific knowledge (Ensley and Hmieleski 2005). Therefore, it is important that TMT members' backgrounds are aligned with different functions which need fulfilling within the team (Ferguson et al. 2016). Entrepreneurial teams of small research-focused firms usually comprise academic scientists who bring with them specific technological competences and some of them may also have managerial experience (Murray 2004; Ensley and Hmieleski 2005). Likewise, in the present context, the TMT comprises a manager who fulfils the leadership role and a principal investigator who fulfils the scientific role.

At the heart of institutional theory is the proposition that legitimacy enhances organisational performance and reduces the chances of failure (Eisenhardt 1988; Barringer and Milkovich 1998; Eberhart et al. 2014; Khaire 2010). Therefore, by signalling organisational legitimacy firms can attract external funding (Certo 2003; Becker-Blease and Sohl 2015). As was noted previously, under conditions of information asymmetry, markets attend to observable characteristics of firms to infer their unobservable but desirable attributes (Sanders and Boivie 2004). Two important attributes are associated with organisational quality and value, and shape perceptions of legitimacy, namely reputation and status.

The conventional definition of organisational reputation refers to the quality of company's past performance outcomes (Podolny and Phillips 1996). However, such view of reputation is difficult to apply to firms which have limited historical actions upon which their future prospects can be judged. Literature suggests that in nascent firms founding team's reputation is equivalent to organisational reputation (Cohen and Dean 2005). Particularly in smaller firms, status and skill set of TMT tend to become analogous with that of the firm (Zhang and Wiersema 2009).

Similar to reputation, organisational status reflects social rank of its economic actors (Stern et al. 2008). In sociology, the status of economic actors is shaped through relational ties embedded in social systems and is determined by the quality of their affiliates (Stern et al. 2008). Status characteristics influence expectations of performance of assessed actors, and research shows evidence that higher status is associated with higher competences and capabilities, increasing odds of success (Berger et al. 1972).

Together, functional and educational background are related to relevant perspectives that can be applied to the task (Bell et al. 2011). Different dimensions of human capital manifested in educational attainments and professional experience of the main team members reflect conforming legitimacy (Tornikoski and Newbert 2007). Therefore, forming investor opinion around positive TMT-level signals such as experience, education and professional competences is critical to the success of nascent ventures in obtaining capital (Zimmerman 2008).

Since legitimacy is an intangible organisational asset, it cannot be measured precisely, yet can be estimated through proxies (Zimmerman and Zeitz 2002). In the present context, all proxies of legitimacy refer to biographical information included in the application form and hence meet the signal observability criteria, as they are readily visible to decision-makers evaluating firms. In addition, legitimacy signals are credible as they are costly to imitate (Certo 2003). In line with Certo (2003), the primary prediction is that investor perceptions of organisational legitimacy will be affected by cumulated human capital.

According to existing literature, investors are likely to perceive organisational legitimacy as an additive function of individual legitimacy of each TMT member (Cohen and Dean 2005). Therefore, organisational legitimacy is an accumulation of individual legitimacy of team members which is shaped through their respective qualities. Like other types of signals, individual-level legitimacy has to be observable to outsiders and reveal the potential of TMT to create a financially viable business.

In line with existing literature (Cohen and Dean 2005; Higgins and Gulati 2006), TMT legitimacy was conceptualised as a cumulative function of (i) role legitimacy, (ii) resource legitimacy and (iii) intellectual legitimacy, while indicators making up categories of legitimacy are expected to have a complementarity effect. In selecting these three types of legitimacy and indicators comprising respective categories, the extant scholarly work was reviewed on TMT characteristics and their relationship with firm performance. The underlying reasoning is that types of previous experience, advanced qualifications, affiliations with educational institutions and productive output of TMT members are associated with higher quality firms and enhance investors' perceptions of legitimacy.

Role Legitimacy Signals

Legitimacy literature postulates that reputation is a function of visible experience accumulated over the years (Janney and Folta 2006; Lange et al. 2011). One type of reputational organisational legitimacy has been termed role legitimacy. Role legitimacy is associated with TMT members' capacity to assume certain positions within the firm and has been defined as the correspondence of top managers' experience and expertise with key organisational functions (Higgins and Gulati 2006).

The breadth and type of TMT's prior experience have been found to be statistically linked to young firms' growth (Eisenhardt and Schoonhoven 1990), innovativeness (Bantel and Jackson 1989) and ability to raise funds (Walske and Zacharakis 2009). Previous related experience indicates to investors that TMT members have the functional expertise necessary to thrive in the uncertain environment as well as skills to manage and lead complex NPD projects. Additionally, relevant prior experience is a guarantee that the task can be managed appropriately because it is not new to the firm (Ferguson et al. 2016). Specifically, when backgrounds of top management match the assigned roles within the team, it enhances investors' perception of TMT's task competence and the ability to achieve the ultimate organisational goals. Here, role legitimacy is defined as a set of four indicators, namely executive's functional role, organisational tenure, technical experience and entrepreneurial experience.

Executive's Functional Role

In small firms, individuals often have to fulfil more than one functional role. In particular, *"top executives often have experience in multiple functions, although they may have dominant experience in one"* (Hitt and Tyler 1991 p.334). Executives' participation in more than one position within the TMT, the firm or the board, is known as CEO duality. The studies demonstrated inconclusive results concerning the strength and direction of CEO duality-performance relationship (e.g. Baliga et al. 1996;

Boyd 1995; Finkelstein and D'Aveni 1994), concluding that the impact of CEO participation can vary under different circumstances.

A stream of literature within the TMT framework suggested that the breadth of executive's functional experience might explain the differences in the perceived impact of the CEO's participation (Cannella et al. 2008). The upper echelons theory postulates that executive's functional background influences their cognitive perceptions, analytical frameworks and strategic decision-making (Wiersema and Bantel 1992). The expectation hereby is that investors' opinion about TMT's legitimacy varies depending on the CEO's functional role within the team; that is, whether the CEO is a broad generalist or a narrow functional specialist (Bunderson and Sutcliffe 2002).

Broader functional experience of executives enhances their strategic acumen, making them less risk-averse; while narrow functional experience results in the development of deeper perspectives within a specific domain of expertise (Geletkanycz and Black 2001; Cannella et al. 2008; Sine et al. 2006). Kish-Gephart and Campbell (2015) found empirical evidence that CEOs with a general management career track tend to underestimate risks associated with new investments compared to their colleagues with a more narrowly defined functional background. Therefore, the proposition developed here is that the presence of more functionalist science-focused CEOs as opposed to management-focused CEOs (principal investigator-CEO vis-a-vis manager-CEO) will be associated with less potential strategic risk-taking behaviour and will subsequently reduce investor's perceived uncertainty in firms' prospects.

Organisational Tenure

Upper echelons theory gives importance to TMT tenure. TMT tenure is increasingly used as a compound indicator of individuals' task orientation and authority within the firm, which affects their cognitive and behavioural processes, and subsequently organisational outcomes (Hambrick and Fukutomi 1991) such as inventive activity (Wu et al. 2005), NPD experimentation (Miller and Shamsie 2001), changes in corporate strategy (Wiersema and Bantel 1992), financial performance (Miller and Shamsie 2001) and performance conformity (Finkelstein and Hambrick 1990).

In the signalling context, the tenure of TMT members is perceived by investors as a reliable proxy for credibility (Zhang and Wiersema 2009). Prior research found evidence that TMT tenure signals higher firm quality to financial markets at the time of IPO (Cohen and Dean 2005). Longer tenure is an indication of firm-specificity of skills (Harris and Helfat 1997). As such, firm's performance is progressively influenced by task knowledge accumulated by the TMT (Hambrick and Fukutomi 1991). The proposition hereby is that higher TMT tenure will signal higher firm-specific role legitimacy to investors.

Technical Experience

Functional background refers to an individual's prior work history across different functional specialisations (Bunderson 2003). As such, functional background, which is accumulated through previous experiences, reflects expertise and knowledge of individuals in a specific field and shapes their attitudes and cognitive perspectives (Bantel and Jackson 1989).

The primary business function of research-focused biotech ventures concerns development not only of new products and technologies, but also drugs, medical instruments, therapies and diagnostic tools, which requires specialised technical expertise and cross-disciplinary knowledge (Deeds et al. 1999). As a result, in research-intensive industries, high level of technical knowledge indicates TMT's ability to accurately assess commercial viability of new discoveries and divert limited resources towards the most promising ones (Deeds et al. 1999).

Relevant technical experience signals TMTs' prior exposure to similar tasks (Bell et al. 2011). TMTs with relevant technical competency have field-specific practical experience and can efficiently process and react to functional information from within their domain of expertise (Ensley and Hmieleski 2005). Therefore, the presence of TMTs with technical experience signals to investors that the firm embodies functional domain-focused skills and competencies.

Entrepreneurial Experience

Moreover, valuation of new ventures by external funding providers is influenced by TMT's prior founding experience. As noted by Hsu (2007), teams with previous start-up founding experience signal entrepreneurial quality. It was also acknowledged that previous start-up experience has a significant impact on entrepreneurs' ability to successfully commercialise research and innovation (Markman et al. 2008) and achieve financial success (Zhao et al. 2013).

Prior scholarly work established that entrepreneurs learn management and operational skills through the experiential process (Politis 2005) and transfer those skills to subsequent start-ups (Ucbasaran et al. 2009). In addition to having enhanced human capital necessary to develop new ventures, habitual entrepreneurs also benefit from established social network ties which grant them access to extensive financial and managerial resources (Mosey and Wright 2007). Therefore, previous entrepreneurial experience signals that TMTs have acquired specific human and social capital necessary to lead the venture to success (Wennberg et al. 2011).

Resource Legitimacy Signals

Consistent with Higgins and Gulati (2006) the type of organisational legitimacy which is linked with access to strategic human and social capital resources is termed resource legitimacy. It is expected that certain attributes of TMT members such as academic statuses and affiliations, will signal availability of legitimate resources within the firm and will have a positive impact on investors' decisions. The prestige of human capital is assessed through educational and employment academic statuses, such as advanced degrees and titles, which signal abilities of TMT. The prestige of social capital, on the other hand, is appraised through affiliations with high-status academic institutions, which signal quality of acquired knowledge as well as potential access to affiliated partners' resources through network ties.

Signals of education are effective sorting mechanisms in resolving investors' uncertainty regarding firms' quality. Educational degrees are efficacious market signals as they are both easily observable and costly to obtain because in the absence of necessary abilities and qualities awards will not be confirmed by the issuing institution (Certo 2003). In person-perception research, individuals signal their social class through education (Kraus and Keltner 2009). Educational background is also believed to influence task-related attitudes and perspectives, which implies that educational heterogeneity within the team will improve task performance (Bell et al. 2011).

Organisational linkages with reputable institutions via certifications and endorsements have been found to enhance perceived legitimacy of firms in the eyes of external market observers (Baum and Oliver 1991; Booth and Smith 1986). In particular, ties with reputable institutions help resolve the portion of uncertainty when firms confront the liability of newness or smallness. It is well established that academic certifications granted by prior evaluators enhance the level of perceived legitimacy (Sanders and Boivie 2004). Therefore, investors use organisations' affiliations with legitimate partners, such as academic institutions, in the evaluation process of nascent firms' future potential (Janney and Folta 2006).

Through its linkage with knowledge, skills and cognitive ability, educational attainment is expected to be associated with legitimacy, while more advanced degrees or qualifications obtained from elite educational institutions will have an even stronger positive effect due to their perceived exclusivity (Cohen and Dean 2005). To reflect the above reasoning, in the present study resource legitimacy comprises four indicators—elite education, advanced business education, advanced technical education and academic seniority.

Elite Education

Prestigious persons involved in an organisation verify to the market its legitimacy and worth (Certo 2003). Prestigious human capital characteristics are costly to obtain and are therefore perceived as credible signals of quality. Empirical evidence exists that affiliations of TMT members with prominent institutions have a positive influence on investors' perceptions, and enhance the level of trustworthiness they associate with the firms (Burton et al. 2002; Higgins and Gulati 2006; Sauer et al. 2010). Elite education also brings with it an improved access to resources from valuable connections on which to fall back in difficult times and easier formation of networks, leading to exposure of new ideas (Kish-Gephart and Campbell 2015 p.1620). Moreover, elite education forms a perception of the higher social status of individuals.

Prior studies have demonstrated that an educational degree from the elite institution can be an indication of ability (Wiersema and Bantel 1992). Higher status universities tend to have more rigorous admission processes based on potential students' intelligence and achievement, which are human capital characteristics sought after during firms' quality evaluation by financial markets (Podolny 2001; Gomulya and Boeker 2014). The anticipation thereby is that TMT members will be compared based on their affiliations with educational institutions. In line with prior studies (e.g. Stern et al. 2014), academic ranking of universities from which the member of TMT graduated is a direct signal of the status of academic affiliation. The higher is university's rank, the more positive impact it will have on investors' perceptions of firms' legitimacy.

Advanced Business Education

Research shows that managerial skills are favourably received by markets (Finkelstein and Hambrick 1989). Advanced education in business equips TMTs with knowledge about markets and industry-wide skills in disciplines such as finance, accounting, operations and leadership which can be applied in any sector (Patzelt et al. 2009). Wider knowledge broadens their exposure to business practices, forms strategic perspectives, as well as stimulates risk-taking behaviour. Based on their non-industry-specific skills, MBAs are perceived by outsiders as broader generalists (Datta and Iskandar-Datta 2014). The literature suggests that MBA-holders typically outperform their non-MBA TMT colleagues (Bertrand and Schoar 2003; Custodio et al. 2013). Therefore, it is expected that overall TMTs with an MBA degree will help form a positive opinion around the firm's legitimacy (Homburg et al. 2014).

Advanced Technical Education

Advanced technical degree holders develop a more science-oriented cognitive structure during their doctoral training, which subsequently affects individuals' information processing and decision-making (Ding 2011). As a result of their scientific background, PhD-holding TMT members are better methodologically equipped to conduct cutting-edge research and turn it into innovation. PhD-holders also have access to an extensive network of academic connections, which facilitates science- and entrepreneurship-oriented information exchange and knowledge sourcing (Liebeskind et al. 1996). Overall, through its association with a higher professional status, TMT's PhD training credentials will be positively received by venture capitalists.

Academic Seniority

Another factor which is closely linked with legitimate human and social capital within the small venture is revealed by the presence of top academic scientists in the TMT. A number of studies showed that involvement of academic inventors is critical for the survival of nascent high-tech ventures (Jensen and Thursby 2001; Thursby and Thursby 2002).

Scientific discoveries originate from scientists. Since tacit knowledge is difficult to transmit to other parties and largely remains accessible to individuals, maintaining links with lead scientists guarantees continued access to intellectual human capital, which influences venture's success (Darby and Zucker 2003). As Gittelman and Kogut (2003 p.380) observed, *"bridging the disconnect between scientific knowledge and innovation appears to depend on access to individuals who perform both".*

Prior research showed that full-time commitment of academic entrepreneurs enhances firm performance, and increases private sector commercialisation, including patenting and product development activities (Zucker et al. 2002; Siegel et al. 2007), while their own research productivity also gets positively affected (Lowe and Gonzalez-Brambila 2007). Scholarly work also presented evidence that scientific status of team members' signals quality of nascent firms to financial markets (Higgins et al. 2011). Therefore, in situations characterised by information asymmetry, the involvement of the senior academics will be perceived by outsiders as a signal of venture's credibility (Toole and Czarnitzki 2007). Additionally, academic seniority is expected to signal access to a broader network of scientific resources.

Intellectual Legitimacy Signals

Knowledge created in SMEs largely remains tacit and embedded in its scientists (Agarwal and Shah 2014). However, the codification of tacit knowledge can be beneficial to scientists as it allows them to articulate their human capital explicitly in order to be recognised by members of the community (Thorpe et al. 2005). Prior research used two proxies of codified knowledge–publications (Audretsch and Lehmann 2005) and patents (Jaffe 1989; Acs et al. 1992). Literature suggests that external market actors evaluate young firms' intellectual capital based on proxies which capture research output of the scientific team (Zucker et al. 1998).

A number of scholars pointed that competencies ingrained in the scientific team enhance product development outcomes (Leonard-Barton 1992; Henderson and Cockburn 1994). Basic scientific research facilitates product development in high-tech industries (Dasgupta and David 1994), and in particular in biotech, which is characterised by complex knowledge structures (Pisano 1994). Therefore, research productivity of a scientific team is a critical factor behind the firm' commercialisation potential.

The proliferation of academic entrepreneurship triggered the development of a dual perspective towards research by university scientists–whereas traditional academic perspective stimulates publications in the field to establish reputation, an entrepreneurial perspective fosters commercialisation of knowledge and discoveries (Etzkowitz 1998). Thus, the propensity of scientists to concentrate on either publishing or patenting knowledge also signals their 'academic orientation' or 'entrepreneurial orientation'. Individual scientists with high patenting and publishing productivity are often described as star scientists (Han and Niosi 2016).

Evidence exists that the presence of star scientists in the team increases firms' innovative productivity (Kehoe and Tzabbar 2015). Similarly, entrepreneurial academics who engage in the commercialisation of research exhibit higher productivity in terms of journal publications, impact publications, research awards and patents in comparison to their non-entrepreneurial academic peers (Toole and Czarnitzki 2010). Their established reputation within the firm and connectedness to external knowledge networks, makes their involvement imperative for technological gatekeeping and controlling information flows within and between relevant knowledge domains (Tushman 1977). Therefore, academic entrepreneurs bridge discovery and innovation activities of firms (Gittelman and Kogut 2003).

Intellectual legitimacy reflects ventures' propensity to engage in strategic behaviour to produce more tangible outputs in order to portray themselves as real operating organisations (Gartner et al. 1992). Consistent with prior studies (Tornikoski and Newbert 2007), with research publications and applications for patents TMTs can signal new ventures' operational performance. Higher value and productivity of intellectual capital are likely to have a greater appeal for investors due to associated underlying capability (Stern et al. 2008). Additionally, investors use written documents produced by TMT members as part of the application process to assess their intellectual ability to effectively communicate valuation-relevant information (Loughran and McDonald 2014). Hence, the hypothesis is that investors infer intellectual legitimacy of small ventures by attending to the TMT's inventive capacity and academic competence as well as readability of the abstract describing aims and objectives of the project.

Inventive Capacity

Inventors' commercialised research output in the form of patents has potential economic value (Guerrero and Urbano 2014). Evidence exists that high impact research leads to higher patenting rates (Markman et al. 2008). Also, patenting is a result of inventor's willingness to exploit the possible applications and market potential of novel knowledge, so is a signal of their entrepreneurial intentions and thinking (Qian and Acs 2013). As a result, patenting productivity is higher among scientists who engage in applied, as opposed to basic research (Calderini et al. 2007). Academic entrepreneurs often choose to establish their own firms to best appropriate the returns from the knowledge that they generated (Audretsch 2004). As such, TMT's inventive capacity captured by their patenting activity is a signal of productive effort as well as entrepreneurial orientation.

Academic Competence

Affiliation with the scientific community is contingent upon the members' proven ability to generate new knowledge (Dasgupta and David 1994; McMillan et al. 1995). Publishing basic research allows entrepreneurs to demonstrate their high-status academic credentials and maintain a foothold in the scientific community, benefitting from access to knowledge networks within academic institutions (Ding 2011). Therefore, a publication record in academic journals is not only a signal of high-quality research but is also an indication of the membership in the 'science club', which allows keeping up to speed with advancements in science beyond the firm's boundaries (Ding 2011). Exchange of externally-generated information through both formal and informal channels is particularly valuable in rapidly developing industries such as biotechnology (Pisano 1994). Therefore, TMT's competence to publish their research is an indication of research quality and affiliation with the 'science club'.

Abstract Readability

Signalling theory is concerned not only with what types of information are transmitted, but also how. In his classic paper, Hayek (1945) defined dispersion of information as a key efficiency of economic systems. At the core of signalling theory is the notion that efficacious signals have to be both observable and costly to produce. However, there is a stream of scholars who indicated that ordinary, informal communication can have a signalling effect and reduce information asymmetry in the markets (Farrell and Rabin 1996; Almazan et al. 2008; Payne et al. 2013). Due to low costs associated with the production of such signals, they have been coined 'cheap talk' and have been shown in a formal economic model to be perceived as credible signals when senders and receivers have interests in common (Crawford and Sobel 1982).

Firms applying for external funding are required to produce narratives disclosing aims and objectives of projects. Despite being inexpensive to produce, such narratives can bear costs to signallers, as the inclusion of any false information concerning pursued entrepreneurial opportunities will be penalised by financial markets in the future once caught (Moss et al. 2015). Therefore, entrepreneurs have strong incentives to provide true and fair narratives.

In financial contexts, narrative statements signal entrepreneurs' characteristics and intentions (Moss et al. 2015), while readability of statements can be used by investors to gauge the intellectual legitimacy of entrepreneurs. Following Loughran and McDonald (2014 p.1644), readability is defined as the ability to effectively communicate valuation-relevant information. Readability is conceptualised as the level of complexity of a written document and has been widely used in prior accounting and finance literature. The underlying assumption is that more effectively written texts reduce the level of valuation-associated ambiguity (Loughran and McDonald 2014). Hence, more readable texts signal the underlying intellectual ability of TMT members to communicate complex information in a clear way that can be easily understood by the non-specialist audience such as investors.

H2-1a: More observable signals of role legitimacy, resource legitimacy and intellectual legitimacy have a positive effect on the magnitude of initial funding commitment.

H2-1b: More observable signals of role legitimacy, resource legitimacy and intellectual legitimacy decrease the likelihood of funding discontinuation.

Relationship between Efficacy and Funding Allocation Decisions

Signal strength also depends on the extent to which it reflects changes in conditions and is time-relevant (Janney and Folta 2006). Since signal value erodes as the time passes, more recent signals should be perceived by investors as particularly strong and reliable because they transmit up-to-date and timely information.

As was discussed in the previous chapter, signalling literature also defines signals in terms of their temporal attributes, and differentiates between the point and flow signals (DeKinder and Kohli 2008). Since legitimacy categories refer to characteristics of TMT members at a certain point in time, they can be described as point signals. On the other hand, information that has been transmitted over a period of time relates to flow signals and is perceived as an indication of signallers' intentions and abilities (DeKinder and Kohli 2008).

Consistent with prior studies (Janney and Folta 2003; DeKinder and Kohli 2008; Janney and Folta 2006), the proposition here is that since investment process related to new ventures is characterised by high uncertainty, assumptions made based on 'snapshot' information transmitted by point signals need to be supported by flow signals, which provide new and up-to-date information, and hence further help investors make conclusions about the quality of firms. New information conveyed through flow signals clarifies investors' perspectives with regards to how the project is progressing (Janney and Folta 2003) and, therefore, indicates organisational efficacy in carrying out the R&D task.

Additionally, research conducted on goal and adaptive expectation theories suggests that decision-makers' expectations are largely influenced by performance signals due to their perceived association with performance on comparable tasks in the future (Branzei et al. 2004). While signals of success stimulate further efforts towards achieving original goals, signals of failure or underperformance prompt discontinuation of such efforts or trigger reorientation of the initial decisions (Lant 1992; Lant et al. 1992). As such, signals of performance success can activate further support of original initiatives. Consequently, flow signals are hypothesised to be perceived as particularly strong and reliable, because they convey more recent information concerning efficacy and performance (Janney and Folta 2006).

Post-funding Project Duration

The nature of the stagewise funding programme mandates that entrepreneurs receive initial investments to engage in experimentation. Early-stage experimentation allows estimating the prospects of potential future payoff from the project before embarking on larger late-stage financial commitments. Literature suggests that venture capitalists use milestones as an effective signalling device and information acquired during experimentation is treated as a *"continuous public signal that detects unprofitable projects with some probability"* (Bouvard 2012 p.181). Thus, information acquired during experimentation enhances the efficiency of the investment decision-making (Chevalier-Roignant et al. 2011).

Although longer experimentation may increase the accuracy of obtained results, it also defers the period of potential future payoff. In the optimal scenario, the marginal benefit of additional information should exceed the marginal cost of experimentation (Bouvard 2012). Therefore, the sooner the evidence on the potential profitability of the project can be gathered, the more certainly the project can be assessed, improving the overall investment process. In other words, longer project duration will be associated by investors with higher investment risks.

Post-funding Invention Activity

Patent stock is indicative of the strength of the ventures' intellectual property position (Shane and Stuart 2002) and is therefore widely used by venture capitalists in making funding allocation decisions (Baum and Silverman 2004; Lerner 1994). Prior studies found that filing patent applications is positively related to new ventures' propensity to receive venture capital funding (Haeussler et al. 2014). Haeussler and colleagues (2014) argued that information which emerges in the course of evaluation process is equally important and showed support that investors attend to the patenting activity to revise their conclusions about the abilities of nascent firms.

Moreover, Warner et al. (2006) noted that although patents do not guarantee future commercialisation success, they signal technical potential of the technology as well as firms' intention to reduce uncertainty surrounding their productive credentials. Prior studies have shown empirical evidence that patents are significantly associated with the likelihood of funded firms' success (Stuart et al. 1999) and failure (Shane and Stuart 2002). Therefore, patent applications convey intrinsic qualities of the projects as well as the new ventures. Patenting activity is particularly important for firms that had no prior awards in the past as the initial investment was intended to help R&D activities take off and develop relevant technical knowledge. The proposition is hereby that firms that seek to reduce uncertainty by engaging in patenting activity are positively viewed by investors.

H2-2: More recent signals of efficacy have a stronger effect on the likelihood of funding discontinuation than signals of legitimacy.

Relationship between Capabilities and Funding Allocation Decisions

Real options reasoning offers a unique heuristic applicable to detecting and assessing capabilities related to exploratory activities which create future opportunities (Bowman and Hurry 1993; Kogut and Kulatilaka 1994b; Kogut and Kulatilaka 2001). Evidence exists that firm-level capabilities have a strong effect on strategic boundary choices (e.g. Leiblein and Miller 2003). Hence, the resource-based and knowledge-based view can enrich real options theory by explaining how firm-level heterogeneity impacts option value (Folta and O'Brien 2004).

The resource-based view postulates that to create positions for sustained competitive advantages firms need to develop a set of unique and inimitable resources, competences and capabilities (Prahalad and Hamel 1990; Barney 1991). It was noted that strategic options emerge through a combination of existing investments, knowledge assets, capabilities and market conditions (Bowman and Hurry 1993; Zhao et al. 2013). Subsequently, under real options theory, organisational capabilities are viewed as strategic platforms for investment in future opportunities (Kogut and Kulatilaka 1994b). Although reputation and expertise are both difficult to build, they are necessary yet not sufficient ingredients for long-term yield from investments in opportunities. Capabilities, on the other hand, can be viewed as a function of both accumulated reputation and expertise, demonstrated through a consistent ability to utilise skills and resources for the achievement of organisational goals (Kogut and Kulatilaka 1994b). Firm's ability to assimilate and exploit relevant knowledge to meet its organisational goals reflects its efficiency in absorbing useful information and has been coined absorptive capacity (Cohen and Levinthal 1990).

The resource-based view extends real options theory by proposing that the benefits of option-like investments in R&D projects are enhanced through learning platforms which they create with the foresight to build up technical expertise (Kogut and Kulatilaka 1994b). Such expertise not only enables accumulation of core competencies in specific technologies (Prahalad and Hamel 1990) but is also linked with wider organisational capabilities for long-term strategic gains, such as the capacity to effectively develop and commercialise new products (Kogut and Kulatilaka 1994b). According to Bowman and Hurry (1993), organisational capabilities developed through learning routines, impact sense-making and recognition of shadow options. Therefore, the ability to recognise shadow options is shaped through a combination of organisational learning and strategic choices. Consequently, firms with greater absorptive capacities are expected to learn more from sequential option-like investments (Cohen and Levinthal 1990).

The above theoretical arguments were summarised by Kogut and Kulatilaka (1994b p.70): *"Flexibility [of option-like investments] is of no value in the absence of the resources required for execution… learning new capabilities is ultimately the most critical investment in opportunity for the* *long haul."* Following this line of logic is the conjecture that investors will attribute perceived differences in firms' absorptive capacities to their differential abilities to recognise and generate options, which will have an impact on investment patterns. However, because capabilities are not easily observable signals, their impact on investment decisions is expected to be weak.

In his paper, Collis (1994) summarised the definitions employed in extant literature to describe the concept of organisational capabilities into three broad categories. The first category defines organisational capability as an ability to carry out key functional activities; the second category relates to the ability to dynamically improve; while the third category refers to the ability to recognise new strategic opportunities (Collis 1994 p.145). To capture these dimensions of organisational capability, three relevant types of capabilities that have received the most attention in the literature dedicated to resource-based theory (Collis 1994; Teece et al. 1997; Zollo and Winter 2002) were identified as R&D capability, intellectual capability and managerial capability, respectively.

According to Collis (1994 p. 145), one of the elements that comprises the definition of capability is that *"it involves the transformation of physical inputs into outputs inside the 'black box' of the firm".* As such, capabilities create value by governing technological efficiency of production activities within firms (Collis 1994). Consistent with such logic, the present research adopts the input-output approach to define the concept of capabilities (Dutta et al. 1999). Under this perspective, firm's activities are modelled as a transformation function of operational resources into practical objectives. High transformational ability is attributable to high functional efficiency, which is equivalent to functional capabilities (Dutta et al. 1999). As was suggested by Cohen and Levinthal (1990), in addition to firm's knowledge stocks, firm's absorptive capacity also comprises absorptive capacities of its individual members. In line with this reasoning, R&D capability reflects firms' absorptive capacity, intellectual capability reflects principal investigators' absorptive capacity, while managerial capability reflects managers' absorptive capacity. That is, R&D capability relates to firm-specific ability to carry out functional processes, intellectual capability refers to lead scientists' ability to dynamically deploy their own knowledge stocks, while managerial capability denotes the managers' ability to dynamically recognise new opportunities and implement strategic change. The underlying rationale guiding conceptualisations of each capability is discussed in detail consecutively.

R&D Capability

Functional capabilities develop within specialised domains and operational activities of firms (Amit and Schoemaker 1993) and reflect the firms' ability to do specific things (Hall 1993). Hence, functional capabilities utilise local knowledge and abilities embedded in firms' daily processes (Henderson and Cockburn 1994). Research and development is a type of functional capability (Verona 1999), and because of its development within the firm-specific context, it creates a form of competitive advantage which is difficult to replicate (Barney 1991).

Empirical evidence demonstrated the positive effect of R&D, or technological, capability on performance outcomes such as innovation (Yeoh and Roth 1999), start-ups' performance expressed as sales growth (Lee et al. 2001), entrepreneurial wealth (Deeds 2001), and the amount of capital raised during the initial public offering (Deeds et al. 1997). In addition, prior scholarly work demonstrated that firm's innovative output positively affects financing decisions of capital markets (Atanassov et al. 2007; Liu and Wong 2011).

R&D capabilities have been defined as a unique combination of accumulated patents, technological know-how and operational skills (Lee et al. 2001) that enhance product development outcomes (Henderson and Cockburn 1994; Verona 1999). Such capabilities are core to the success of technology-intensive firms (Henderson and Clark 1990; Tushman and Anderson 1986) and start-ups in particular (Chandler and Hanks 1994; Shrader and Simon 1997).

The uniqueness of R&D capabilities is attributed to the role of learning-by-doing, which makes such capabilities difficult to imitate (Irwin and Klenow 1994), thereby creating performance advantages (Dutta et al. 1999). An importance of firm's previously accumulated tacit knowledge suggests that R&D capability is a manifestation of firm's absorptive capacity (Cohen and Levinthal 1990). Consistent with this view, the conceptualisation adopted here expresses R&D capability as an absorptive capacity which allows to turn research into innovation and then marketable products.

Principal Investigator's Intellectual Capability

Intellectual capital has been described by prior research as cumulated knowledge, expertise, intangible assets and know-how that firms employ to gain sustained competitive advantage (Nahapiet and Ghoshal 1998; Youndt et al. 2004; Teece 1998). It has been defined as *"resource and capability for action based in knowledge and knowing"* (Nahapiet and Ghoshal 1998 p.245). Existing literature has postulated that embeddedness of dynamic capabilities in firms' operational procedures triggers knowledge creation through a learning process (Huber 1991). Therefore, the ability to learn creates a link between intellectual capital and dynamic capability, whereby efficient transformation of knowledge leads to performance improvements (Hsu and Wang 2012).

Theories of intellectual capital tend to delineate the concept as comprising three distinct yet interrelated elements, namely human, organisational and social capital, which operationally refer to individuals, organisational processes and networks as units of analysis, respectively (Subramaniam and Youndt 2005; Reed et al. 2006). Combinations of knowledge stock and skill set possessed by individuals are associated with stronger cognitive ability, which leads to productivity and efficiency in task completion (Davidsson and Honig 2003; Hitt et al. 2001).

Knowledgeable employees are a unique asset in high-tech firms, and their effective decision-making processes lead to sustained firms' performance (Hsu and Wang 2012). Enhancement of human capital through the accumulation of firm's individual members' specialised know-how first increases job performance and then firm's performance (Hsu 2007). As such, intellectual capability, or 'smartness', refers to *"the intelligent mobilisation of cognitive capacities"* for the successful operation of organisations (Alvesson and Spicer 2012 p.1195).

Based on the above reasoning and in line with the theory of entrepreneurial absorptive capacity proposed by Qian and Acs (2013), the conceptualisation of intellectual capability adopted here reflects the absorptive capacity of a lead scientist within the firm to dynamically capitalise and improve available intangible resources and know-how for generation of new valuable knowledge.

Managerial Capability

Early work on managerial capabilities defined such competence as a combination of complementary analytical and intuitive skills (Stamp 1981 p.19). Managerial capability enables orchestration of organisational processes of integration, direction, utilisation and reconfiguration of resources (Day 1994; Henderson and Cockburn 1994). Although the concept of managerial capabilities has been examined from multiple theoretical and empirical angles, the research has converged on one universal conclusion—managerial capabilities are a source of sustained competitive advantage (Hall 1993; Fortune and Mitchell 2012).

Managerial capability manifested through the ability to direct organisational mission has been found to have a positive impact on research productivity (Henderson and Cockburn 1994), innovation (Yeoh and Roth 1999), financial performance (Zollo and Singh 2004) and new product development (Iansiti and Clark 1994). Capabilities comprise a number of distinct knowledge dimensions, including employee-specific skills, technical systems developed through organisational routines and managerial systems (Leonard-Barton 1992). It is the role of managerial systems to interpret and integrate individual and technical knowledge dimensions into a cohesive whole, which suggests a higher-order capability (Day 1994).

Managerial capability has been attributed to the ability to dynamically recognise new strategic opportunities (Collis 1994). Consequently, the body of work that drives the conceptualisation adopted in present research is that of dynamic managerial capability. First, dynamic managerial capabilities are unequivocally linked to the principles of entrepreneurship (Helfat and Martin 2015) because entrepreneurially minded managers create markets by reconfiguring organisational resources and routines (Teece 2012; Zahra et al. 2006). Secondly, dynamic managerial capabilities share the same characteristics with the broader concept of capabilities (Helfat and Martin 2015). A capability is defined as "*the capacity to perform a particular activity in a reliable and at least minimally satisfactory manner*" (Helfat and Winter 2011 p.1244). By extension, a dynamic managerial capability is directed towards achieving an intended organisational goal through orchestration and reconfiguration of resources and routines and deliberate deployment of skills (Helfat and Martin 2015).

H2-3a: In contrast to more observable signals of legitimacy, less observable signals of R&D, intellectual and managerial capability have no effect on the magnitude of initial funding commitment.

H2-3b: In contrast to more observable signals of legitimacy, less observable signals of R&D, intellectual and managerial capability have no effect on the likelihood of funding discontinuation

Effect of Attention-Distorting Signal Categories on Funding Allocation Decisions

Boisot and Canals (2004) in their paper on information theory developed theoretical propositions concerning how data are converted into information and then knowledge. According to the authors, the behaviour of economic agents is driven by the principles of least action and rational deployment of scarce resources. Economic agents first use perceptual filters to attend to certain stimuli in a given situation, which then get registered as data and converted to information through conceptual filters (Boisot and Canals 2004).

Both perceptual and conceptual filters are shaped by a combination of cognition, expectations, prior knowledge, memories, values and emotional dispositions. Agents' information processing capacity is located in a situation, which they subjectively interpret by applying those filters. Hence, selection of stimuli is likely to be hindered by personal style and preference more than by decision rules (Boisot and Canals 2004 p.54). Also, signalling properties are known to be amenable to agents' critical reception (Lampel and Shamsie 2000). When there is an established system of preconceived beliefs concerning the importance of certain signals, decision-makers may gravitate from intended signals and cognitively weaken their signalling power in favour of more salient, attention-distorting signals (Branzei et al. 2004).

The proposition asserted here is that investors are more receptive to information which is relevant to their internal agenda, such as project and portfolio characteristics. These factors are expected to be perceived as more salient and, therefore, act as distortion mechanisms, diverting funders' attention from other signals.

Project Appeal Characteristics

Scholarly work on signalling theory postulates that among other factors, interpretation of signals is also influenced by the receivers' schemata, which is predominantly constructed by analysing competition and is rigid to incorporating changes that occur in the signalling environment (Heil and Robertson 1991). Therefore, the assertion being made is that certain types of projects will be perceived as more appealing based on expectations formed through the historical performance of market incumbents that certain categories of projects tend to perform better than others.

Alternatively, evaluators may seek to fund certain types of projects which have been outlined in the government's agenda as priority areas for research. Either way, the underlying conjecture is that projects' scope and category are more likely to get selected by decision-makers' perceptual filters due to their salience.

Project Scope

The value of options is determined by the scope of opportunities they open (Kogut and Kulatilaka 1994b). Project scope reflects depth and breadth of prospective opportunities as well as firm's expertise in leveraging such opportunities (Sorescu et al. 2003). Subsequently, project scope signals potential attractiveness and competitiveness of the product being developed by the nascent firm (Tornikoski and Newbert 2007). As such, investment choices are to an extent dependent on project scope, which defines target markets and technical boundaries of R&D initiatives (Adner and Levinthal 2004b).

Broad project scope is an indication of greater chances for successful commercialisation as innovation efforts can be translated to a wider number of applications (Sorescu et al. 2003). Narrow project scope, on the other hand, signals a distinct yet restricted stock of core capabilities that can impose rigidities on innovation activities (Leonard-Barton 1992). Therefore, investors may infer that narrow project scope is a result of firm's limited expertise. When investors have explicit commercialisation agenda in place, projects with a broader set of potential applications are more valuable than projects with a narrow set of applications (Kogut and Kulatilaka 1994b).

Project Category

Membership in certain categories can also have signalling properties, even if such properties are not intentional signals, but taken-for-granted attributes (Negro et al. 2014). Belonging to a category can have strong signalling value and be relevant in particular situations such as during the screening process (Negro et al. 2014).

Prior research found that category signalling is explained by the theory of collective reputation, whereby firms belonging to certain groups may benefit or suffer from historical quality attributed to their predecessors (Tirole 1996). Such studies posit that collective reputation is more salient than individual reputation and, therefore, has a stronger signalling value (Negro et al. 2014). Also, prior research found that the evaluation of economic actors is shaped through the process of actuarial prejudice, whereby their perceived chances of success are determined by the perceived chances of success of a group to which they belong (Kiesler 1975). Following this logic is the assertion that certain categories of projects will be viewed by investors as more appealing than others.

H2-4a: Directly relevant project appeal characteristics have a stronger effect on the magnitude of initial funding commitment than legitimacy signals.

H2-4b: Directly relevant project appeal characteristics have a stronger effect on the likelihood of funding discontinuation than legitimacy signals.

Existing Portfolio Characteristics

Moreover, portfolio structure may have a significant signalling effect. Decision makers' attention is directed not only to potential new options, but also pre-existing and ongoing options in the portfolio (Barnett 2008). Under ROR, the value of a new option is determined in light of pre-existing options in the portfolio. For investors, firms with previously created options might be positively perceived due to their prior experience developing similar R&D options, which might have scope-increasing potential (McGrath and Nerkar 2004). Such competing demands for the limited attention of decision-makers tend to crowd out the exploration of new opportunities in support of exploitation of existing strengths (March 1991).

Prior funding allocation is a strong contextual cue indicating that government venture capitalists have evaluated the firm previously and came to the conclusion that it is worth an investment. This proposition is consistent with prior findings (Bowman 1963) that own past decisions tend to be incorporated into a system of present decisions, whereby decision rules are derived from past behaviour. As noted by Bowman and Hurry (1993 p.766), organisational investment behaviour contains an element of inertia triggered by hysteresis—the spillover effect of past investments.

Therefore, through intuitive sense-making in the presence of sunk costs, investors are inclined to hold on to pre-existing investments and decline new investments (Dixit 1992).

H2-5a: Previous funding allocation decisions have a stronger positive effect on the magnitude of initial funding commitment than legitimacy signals.

In addition to portfolio effects, the magnitude of initial commitment in the opened option is expected to have an effect on the subsequent funding allocation decisions. Existing studies on real options indicate that propensity of making the withdrawal decision is lower when initial sunk costs are large (O'Brien and Folta 2009), when environmental uncertainty and market volatility are high (Belderbos and Zou 2009; Moel and Tufano 2002), or when options in the portfolio are correlated and create economies of scope for learning through simultaneous exploration (Vassolo et al. 2004).

With regards to R&D projects specifically, the continuation decision will be influenced by the magnitude of incurred development costs, the expected future cash flows, determined by perceived market size and share, as well as on updated information indicating the value of the R&D project (Newton et al. 2004).

H2-5b: Previous funding allocation decisions have a stronger negative effect on the likelihood of funding discontinuation than legitimacy signals.

Part II Conceptual Models

To sum up, the primary proposition developed in Part II analysis is that TMTs' different characteristics signal their legitimacy which minimises investors' uncertainty in firms' underlying quality. First, TMTs signal the availability of necessary human and social capital resources via academic statuses and affiliations. Second, TMTs signal their ability to fulfil managerial and scientific roles within the firm via previous experience and relevant expertise. Third, TMTs signal their intellectual capability through research output and ability to effectively communicate valuation-relevant information. Taken together, these signals of legitimacy enhance investors' perceptions of firms' potential to thrive in volatile conditions (Suchman 1995). Figure 4-2 depicts a configuration of tested relationships related to investors' Phase I decision-making, whilst Figure 4-3 concerns the decision-making process at Phase II, which also includes signals of efficacy.

Figure 4-2: Conceptual model IIa

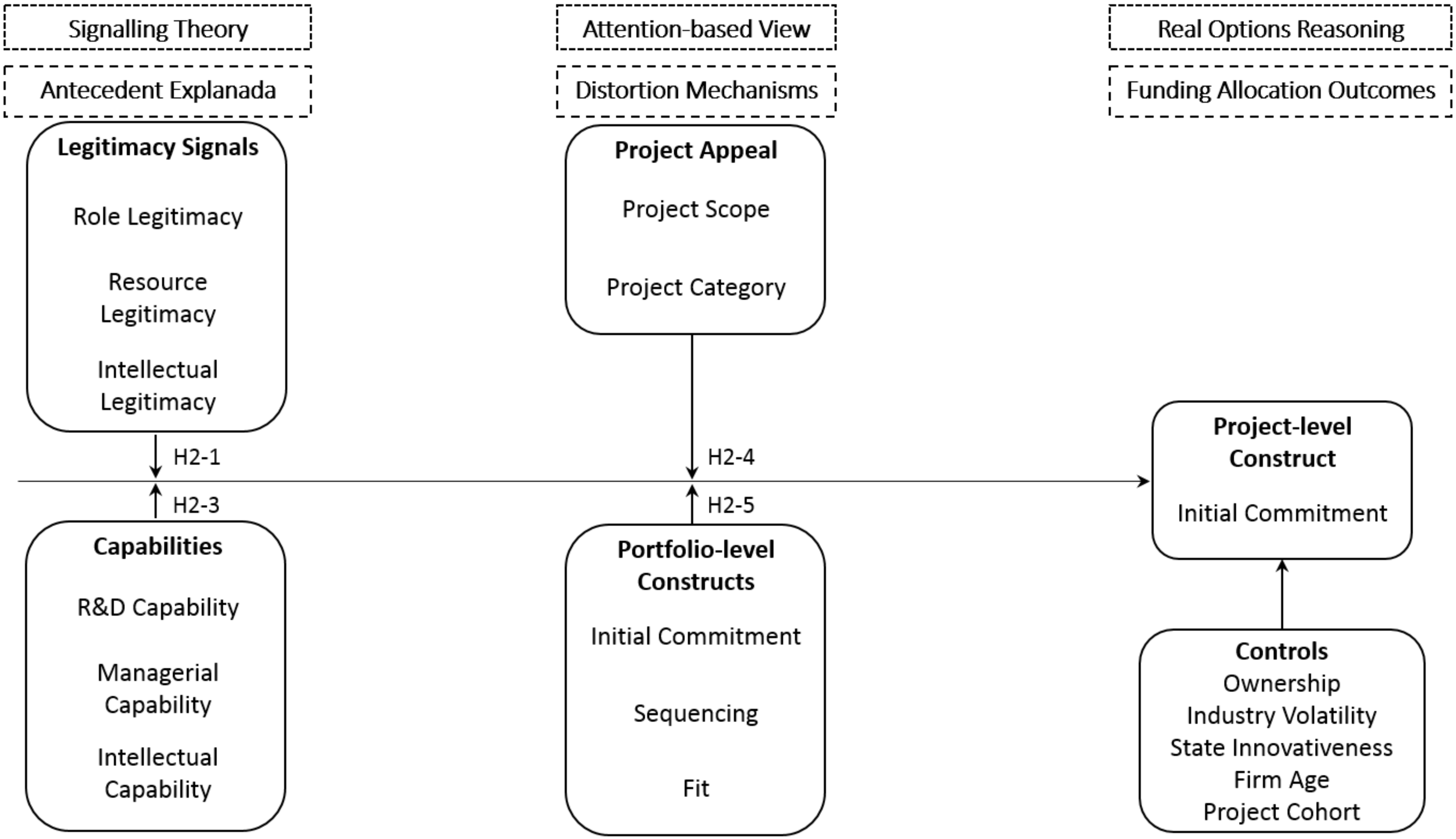
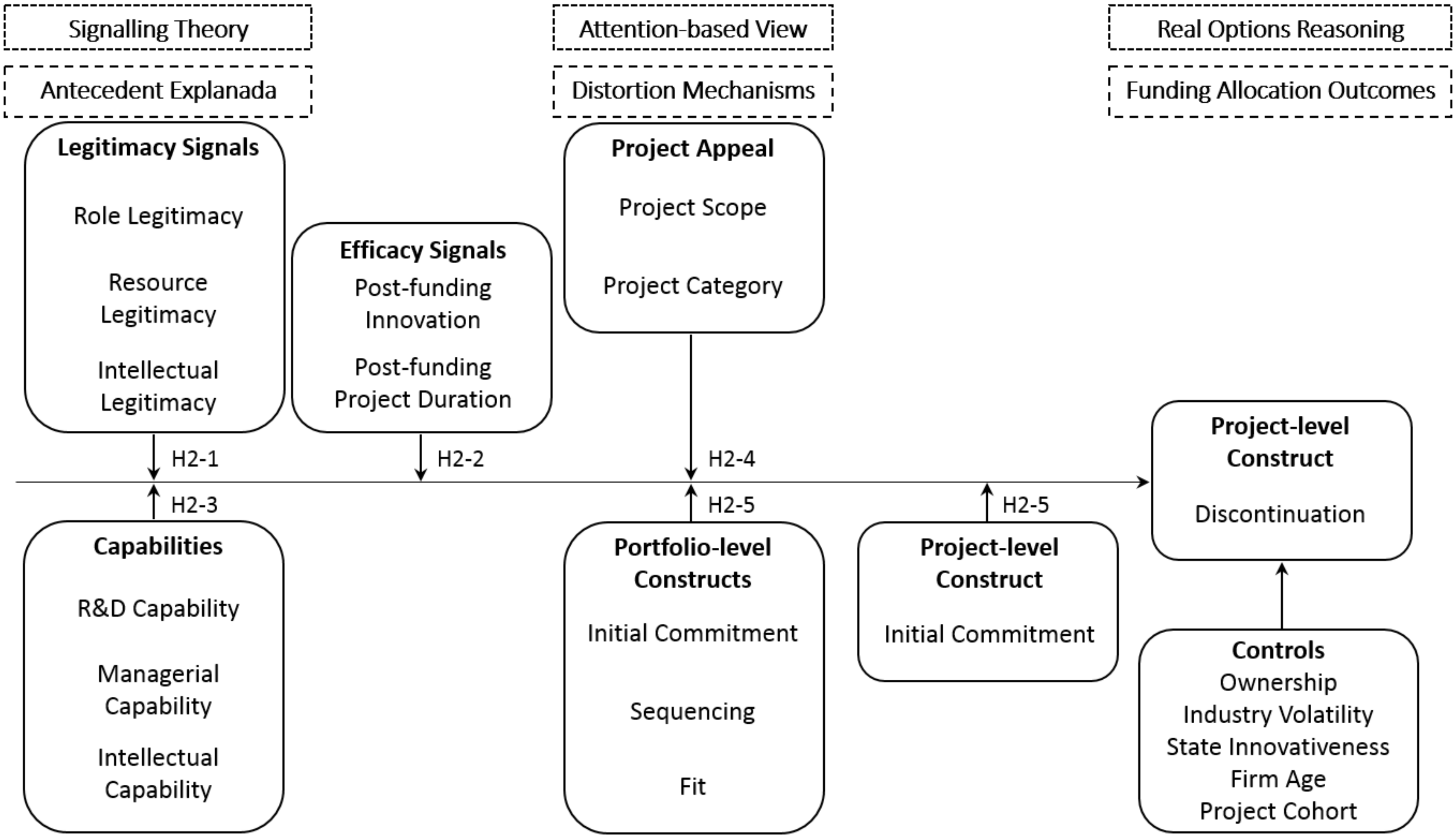


Figure 4-3: Conceptual model IIb



4.4 Part III: Analysis of Complementarities of Real Options Reasoning and Signalling Perspectives to Explain Consequences of Government Venture Funding

The primary objective of the present section is to combine Part I and Part II analyses presented earlier in a coherent model. As such, Part III tests complementarities of ROR and signalling theories in predicting investment yield and long-term firm performance in the context of government venture funding. The core research questions addressed in Part III are: (i) 'Do effects of ROR elements hold in the presence of firm-level factors?', (ii) 'How accurate are signals used as selection criteria for funding allocation decisions at predicting investment yield and long-term firm performance?' and (iii) 'Which configurations of capabilities affect performance?". In addressing these questions, the underlying conceptual foundations have been explicated in the following three sections.

Effect of Funding Allocation Outcomes on Long-term Performance in the Presence of Firm-level Factors

There is an increasing appreciation in the literature on ROR that present statistical models predicting performance implications of real options investments tend to omit firms' skills, competences and capabilities which are also determinants of competitive advantage in firms (Driouchi and Bennett 2012). Reuer and Tong (2007) posited that performance outcomes of real options are influenced by real options investment decisions as well as the implementation of real options, which can have independent and combined effects. The empirical evidence demonstrated that firm-level heterogeneity in skills and capabilities creates differences in management and implementation of real options, which significantly contributes to the variance in the value created by options (Tong and Reuer 2006).

Although managerial and organisation capabilities influence implementation of real options, the current state of research is limited in understanding their role in affecting prescriptions of the investment theory, calling for more work outlining boundaries of real options reasoning from the practical perspective (Reuer and Tong 2007). In particular, firms that had previously opened options might have acquired real options management knowledge and developed a specific set of skills and capabilities necessary for their successful implementation. Therefore, the unequivocal inclusion of firm-level differences such as intangible assets and tacit knowledge in the economic model can project a coherent view of real options performance implications in the organisational setting.

Whereas Part I looks at how the presence, absence and structuring of real options affects performance, Part III extends such inquiry by explicitly incorporating firms' skills and capabilities. Part III analysis merges financial theory with a resource-based view of the firm in a unified model to examine their simultaneous impact on performance heterogeneity of real options. As such, the intention is to test whether real options theory predictions hold in a more 'practical' setting, which also takes account of firm-level factors. Therefore, the key objective here is to move beyond the isolated testing of core elements of ROR and conduct an additional robustness test of insights derived in Part I analysis, thereby showing further support of propositions of ROR. Despite the apparent association of firms' attributes with competitive advantage, the assertion is made that the predisposition of resource allocation outcomes to affect performance in specific ways established in Part I analysis, is unlikely to change significantly in the scenario which closer reflects real life.

H3-1: Effects of ROR elements on investment yield and firm performance continue to remain significant in the presence of firm-level factors.

Relationship between Signals and Long-term Performance

Signals communicate useful information about economic agents' underlying qualities. However, interpretation of signals can be complicated by contextual factors as well as recipients' experience and frames of reference. In particular, interpretation of signals transmitted by firms operating in nascent or niche industries is problematic. The early years of nascent firms are characterised by fluid entrepreneurial processes which emerge as a result of learning-by-doing. Thus, as Sapienza and Gupta (1994) noted, task uncertainty, defined as the discrepancy between required information and possessed information necessary to perform a task, is greater for early-stage ventures working on highly innovative projects.

Such emergent nature of entrepreneurial practices coupled with task uncertainty makes it difficult to define ex-ante the desired list of skills and abilities of economic players in nascent industries, further magnifying information asymmetry (Zahra and Filatotchev 2004). Given that emerging industries face greater unresolved uncertainties, evaluators try to project their future course of development by relying on memories of historical performance of established industries (Zahra and Filatotchev 2004). However, emerging sectors and industries often take their own development path, shaped through interactions of nascent social actors, which may be independent of the rules of the game followed by established industries. Nevertheless, research suggests that receivers are inclined to attend to the same signals upon which they informed their prior choices and decisions (Cohen and Dean 2005). The propensity to imitate past decisions, driven by organisational routines, can impose a so-called 'bandwagon effect' on interpretation practices of signals, which may or may not be accurate (McNamara et al. 2008). As a result, overreliance on prior knowledge leads to misconceptions and subsequent misinterpretation of signals.

Ambiguity involved in new ventures' evaluation makes investors predisposed to heuristics and biases. Despite their ability to operate efficiently under time constraints (Payne et al. 1988), heuristics can also introduce errors (Tversky and Kahneman 1974). One of the most prevalent biases in investment context is that of overconfidence, which can be manifested in the increased propensity to overestimate the likelihood of occurrence of future outcomes or validity of own knowledge, resulting in impaired decision-making (Griffin and Varey 1996). Zacharakis and Shepherd (2001) showed evidence that overconfidence negatively affects venture capitalists' decision accuracy. Among other factors, the authors found that overconfidence can surge when decision-makers automatically process familiar information relevant to the decision and refrain from questioning existing knowledge and seeking new information (Zacharakis and Shepherd 2001). A study by Shepherd (1999) also provided empirical evidence that the accuracy of venture capitalists' introspection is limited.

Following this line of inquiry, investors' decision-making is analysed to determine its accuracy. In sum, the expectation is that there is a discrepancy between expected and real association of firms' attributes with anticipated performance outcomes, which adversely affects decision accuracy and subsequently upside potential of investments.

H3-2: There is a discrepancy between perceived and actual effects of signals on investment yield and firm performance.

Relationship between Interactions of Capabilities and Long-term Performance

The classical theory of organisational rationality postulates that firms' three major components–input activities, technological activities and output activities–are interconnected and require tailored aligning (Thompson 1967). That is, "*the inputs acquired must be within the scope of the technology, and it must be within the capacity of the organisation to dispose of the technological production*" (Thompson 1967 p.19). The capabilities investigated in this study reflect these three component activities: intellectual capability of the PI represents a critical input to the entrepreneurial value-creating process, R&D capability relates to the technological scope, whilst managerial capability is directed at producing outputs.

Similar to other organisational processes and activities, functional and managerial capabilities interact in a complementary yet subordinate manner (Fortune and Mitchell 2012). Amit and Schoemaker (1993) expressed that complementarity of capabilities occurs when the magnitude of one capability increases the strategic value of another, whereas substitution occurs when the magnitude of one capability decreases the strategic value of another.

In the resource-based view of the firm, the rent producing capacity of organisations is contingent upon the unique combination of resources and capabilities and the extent to which they overlap (Amit and Schoemaker 1993; Barney 1991). However, complex interactions between capabilities, although difficult to imitate by competitors, sometimes cannot be apprehended even by the firms possessing them, increasing ambiguity of organisational processes (Reed and DeFillippi 1990).

As a result, the broad assertion presented here is that capabilities may have a direct as well as an interactive effect on superior firm performance, with unique combinations causing complementarity or substitution effects. Given the expectation that firms will need different configurations of capabilities depending on their experience in implementing real options, the posited hypothesis is non-directional.

H3-3: The interactions between capabilities have both complementarity and substitutions effects on investment yield and long-term firm performance.

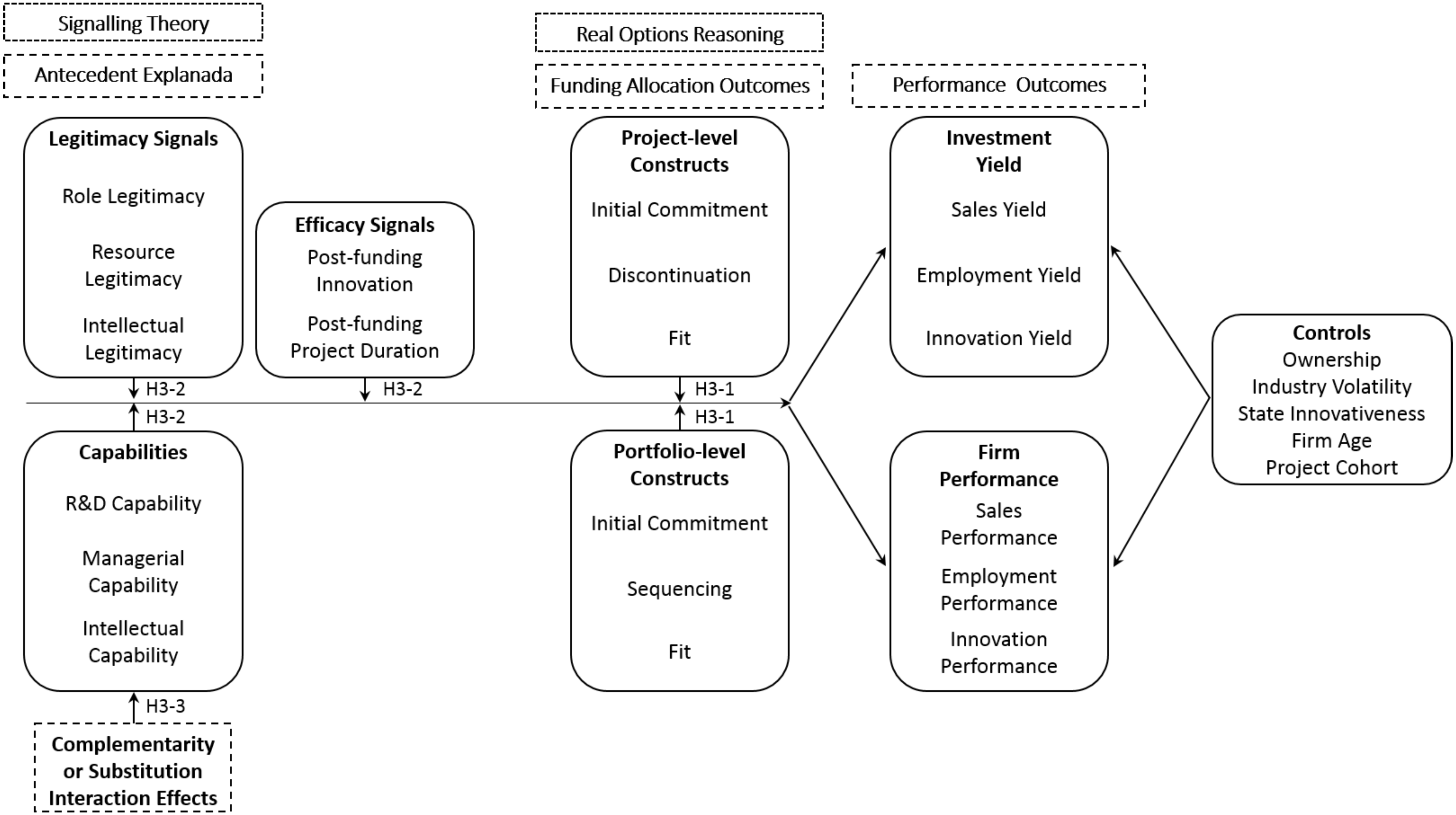
Part III Conceptual Model

Figure 4-4 presents the conceptual model guiding Part III analysis. It combines propositions of ROR and signalling theories in a unified framework to investigate their simultaneous effects on investment yield and firm performance, and specifically investigates direct as well as interaction effects of three types of capabilities.

4.5 Concluding Remarks

This chapter presented theoretical frameworks guiding the present research. To address different directions of research questions, analytical foundations are elaborated in three separate parts. First, hypotheses pertaining to real options theory are developed to investigate the role of distinct ROR elements in influencing long-term performance. Next, the conceptual model examining the effects of signals and attention-regulating mechanisms on funding allocation outcomes is expressed in a series of conjectures. The final part presents a unified framework to test the impact of financial decisions and firm-level heterogeneity on performance.

Figure 4-4: Conceptual model III



Chapter 5 - Research Methodology

5.1 Introduction

With philosophical assumptions informing the choice of methodological approach, this chapter first outlines the premises of the driving scientific research paradigm, which formed the basis for the research design formulation. Next, the sampling and database development procedure is described, followed by the explanation of operationalisations and measures used to construct variables. The chapter concludes with a section on analytical approaches and statistical tools that were employed to examine collected data.

5.2 Scientific Research Paradigm

Questions pertaining to the philosophical understanding of the social world cannot be separated from the principles of how business research is conducted (Bryman and Bell 2011). Therefore, the first step to devising a research methodology requires delineation of researcher's philosophical positions that place the project in context and that way inform the choice of research design and strategy decisions.

Research Philosophy – Post-positivism

Research is a complex process of knowledge development and at multiple stages of that process, the researcher needs to make assumptions about the nature of knowledge. These assumptions are crucial in dictating the choice of research strategy and method, and because they are inherent to the researcher's understanding of surrounding reality, they represent the philosophical position (Deshpande 1983). Two fundamental components comprise the research philosophy— namely, ontology and epistemology, and their understanding helps researchers select and justify the most suitable methodology and develop a coherent research strategy and design.

Ontology refers to the lens through which the researcher perceives the world. Fundamentally, there are two ways to view reality—through the objectivist lens, which stipulates that social phenomena have the exogenous existence of the social elements affected by it, and through the subjectivist lens, which maintains that social phenomena are shaped through interpretations of the social actors (Saunders et al. 2012). Epistemology, on the other hand, is concerned with what type of knowledge is viewed as acceptable in a respective research field (Bryman and Bell 2011).

The four most widely adopted philosophies in the business and management area are positivism, realism, interpretivism and pragmatism. In comparison to the other three paradigms, pragmatism is not dominated by any particular philosophical stance, but instead the choice is driven by whether a certain ontological or epistemological position helps achieve research objectives and dictates the methodology that better fits the nature of the research questions and context (Saunders et al. 2012). As such, pragmatism is driven by the practicality of applied research and is based upon multiple mixed positions. Table 5-1 summarises the underlying principles of three distinct research paradigms.

Table 5-1: Summary of the dominant philosophical paradigms of business and management research

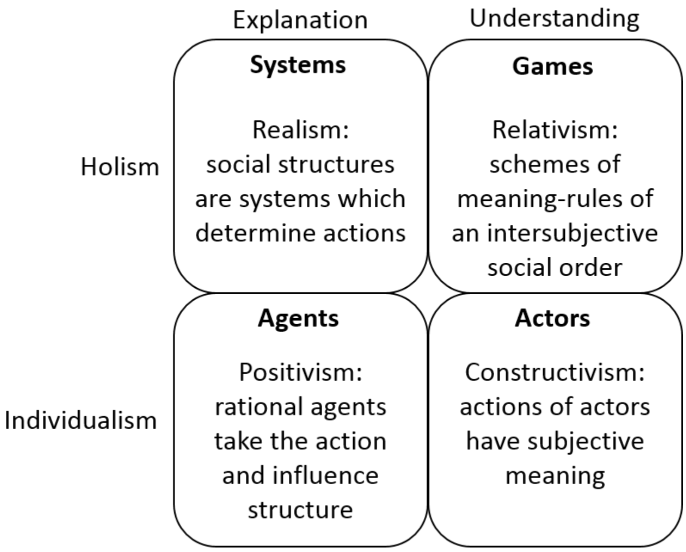
	Positivism	Post-positivism	Interpretivism
Ontology: nature of reality	• Naïve realism • External • Objective • Independent	• Critical realism • Imperfectly external • Modified objective • Interpreted by social actors	• Constructivism/Relativism • Subjective • Socially constructed
Epistemology: nature of knowledge	• Observable phenomena • Data and facts • True results • Causality • Law-like generalisations	• Observable phenomena • Data and facts • Probabilistically true results • Multiplicity of theories for the same fact • Laws context-specific and open to revision	• Subjective meanings • Social phenomena • Details of situation • Opportunity structures • Ideal types
Axiology: nature of values	• Dualism: observer-observed independent • Detachment • Researcher is value-free and objective	• Dualism: observer-observed independent • Detachment • Researcher is value-laden and biassed	• Non-dualism: observer-observed interdependent • Interaction • Researcher is value-bound, part of the phenomenon
Goal	• Explanation	• Explanation	• Understanding
Methodology	• Observation • Quantitative • Mostly induction (knowledge produced)	• Observation • Mixed methods • Mostly deduction (knowledge derived)	• Interpretation • Qualitative • Mostly inuction (knowledge emergent)
Data analysis	• Analysis ‘by variables’ • Structured • Large samples	• Analysis ‘by variables’ • Mixed tools	• Analysis ‘by cases’ • In-depth • Small samples

Source: Adapted from Saunders et al. (2012 p. 140) and Corbetta (2003 p.14)

The current research project is built on the premise that no philosophy is superior or inferior to any other. Although each school of thought has a point to make, each suffers from certain limitations that have implications for knowledge accumulation in the field of management science (Gill and Johnson 1997). Hence, the choice of philosophical position largely depends on the research problem and its objectives.

One of the proposed ways of looking at the philosophical paradigms is by distinguishing between the ‘top-down’ and ‘bottom-up’ approaches by reference to the objectives of the pursued scientific inquiry (Hollis 2006). The schemata presented in Figure 5-1 encapsulates competing traditions of social science, with deterministic 'explanation' and interpretative 'understanding' on the vertical axis, and 'individualism' and 'holism' on the horizontal axis. Whereas 'individualism' reflects actions of agents, 'holism' refers to the way of perceiving individual agents as part of the holistic whole. 'Systems' and 'individual agents' feature in philosophical positions, which are concerned with explanations of the social world, while paradigms encapsulating 'games' and 'actors' are concerned with the understanding of the social world (Hollis 2006).

Figure 5-1: Matrix view of the social world



Source: Adopted from Hollis (2006 p.19)

Given that the current study is evaluative in nature and aims to explain what is happening, seeks new insights, assesses phenomena in a new light and expects to clarify understandings of the problem by addressing the "what" type of questions, the research philosophy reflects the principles of objectivism (Saunders et al. 2012). Specifically, the intention to examine the collective role of individual decision-makers in the government venture capital context, suggests the 'top down' explanation approach. Such approach accounts for individual actions within a holistic working system, which can also have its contribution to the social world independent of the individual agents. However, by comprehending that both systems and individual agents must be present to explain the social worlds, the dividing line becomes blurry (Hollis 2006), calling for a more outward-looking philosophical position.

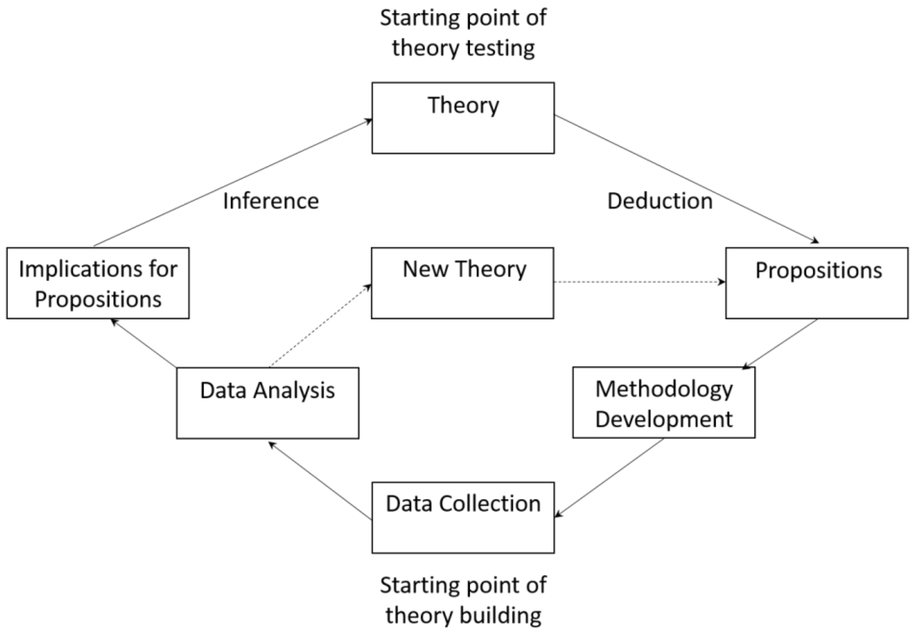
The adopted objectivist philosophical stance is based on the assumption that social phenomena and their meanings have an existence that is rule-governed and separate from social actors (Bryman and Bell 2011). Under this view, the researcher is seen as independent of the studied phenomenon. By adopting the objectivist stance, the study holds that the way firms and individuals behave is driven by their adherence to certain structures and procedures, and although there is internally imposed heterogeneity among social actors, the essence of their functioning is universal across all industries and countries.

Although objectivity is an ultimate ideal goal, it is recognised that researcher's experience and interpretation of the surrounding world can have an effect on research outcomes (Hunt 1993). As such, the position adopted in the current project reflects the principles of the critical realist ontology, which evolved from naïve realist thinking of logical positivism (Corbetta 2003). The positivist doctrine assumes complete and unbiased objectivity of the researcher during the process of gathering and analysis of facts necessary to provide the basis for the generation of laws (Bryman and Bell 2011). In contrast, by acknowledging that it is impossible to fully exclude own values because they are deeply embedded in cognitive processes, the present piece of work adopts a post-positivist logic. Here, the step is taken away from the claims under a value-free perspective and instead the emphasis is placed on achieving value-neutrality as a result of comprehension that interpretation is biassed and theory-laden (Hunt 1993). As such, under the critical realist ontology, cause-effect relationships exist in the external reality, but that reality is imperfectly knowable and objective knowledge can only be approximately achieved (Corbetta 2003). On the epistemological side of the philosophical position, the process of knowledge derivation is enabled through rationalisation and formal logical reasoning and organisations are seen as aggregations of nested levels of stable constructs (Donaldson 1996). However, while both positivist and post-positivist schools of thought agree on the nature of theory, describing it as systematically connected laws, critical realists postulate that it is not only an observed regularity of the studied phenomena, but rather a causality, which may vary across different contexts (Hunt 1983). Therefore, the process of knowledge derivation is focused on exploring the links between multiple theories that are believed to contribute to the studied phenomenon.

Approach Selection – Deduction

When designing the research strategy, explicit reasoning concerning the development of theory needed to be adopted. Two approaches to differentiating between true and false facts are referred to as induction and deduction: the former approach utilises empirical findings to make conclusions, while the latter uses logical reasoning (Ghauri and Gronhaug 2002). As depicted in Figure 5-2, induction is concerned with inferring facts and ideas that precede theory building, whereas deduction is interested in scrutinising the consequences of a theory to confirm or refute its validity in relation to a specific phenomenon or context. The fact that theories tested in the current research are derived from existing academic literature and research propositions are developed a priori indicates that a hypothetico-deductive approach is followed (Hunt 1983).

Figure 5-2: The logic of the research process



Source: Adopted from De Vaus (2001 p.8)

Deduction entails a number of important attributes (Saunders et al. 2012; Bryman and Bell 2011). First, causal relationships between concepts and variables are sought to be explained by the use of a highly structured methodology to enable replication and warrant reliability. Then, concepts need to be operationalised in a way that allows to measure them via facts and quantitative data. Operationalisation is informed by precise definitions of the phenomena and by breaking down the research problem into smaller more easily understood elements. Such reductionist approach is necessary to observe how the variables in question are behaving in a simplified real-world environment (Remenyi et al. 1998). After reducing the problem, the representative sample of appropriate size needs to be selected through techniques such as probability sampling to ensure generalisability of findings. However, the findings of the deductive research will not be generalisable unless the research has been replicated a number of times in different relevant contexts (Remenyi et al. 1998).

Deductive reasoning is concerned with drawing logical conclusions from observed evidence. Hence, the research strategy was structured in the following steps: (i) deduce a hypothesis from the theory, (ii) express the relationships in operational terms, (iii) test the hypothesis, (iv) examine the outcome, and finally, (v) modify the theory in light of the findings (Saunders et al. 2012). In this respect, deduction reflects the principles of scientific approach which emphasises the centrality of theory and its empirical testing (Donaldson 2005) and hence goes in line with the post-positivist position adopted in current research.

5.3 Research Design

Once the underlying philosophy and research approach have been established, the next step is to outline research design and strategy. Each element of the methodology was carefully formulated as to accommodate the post-positivist epistemology and objectivist ontology embedded in the nature of the research phenomenon, while research design decisions and tactics reflect the overarching principles of the scientific paradigm.

Methodology Selection – Quantitative

The choice between qualitative and quantitative methods reflects different perspectives on the nature of knowledge and the purpose of research (Ghauri and Gronhaug 2002). Positivist epistemology and deductive approach, often mandated through the use of thoroughly planned data generation procedures, are closely associated with quantitative research methods. The studied phenomenon is expressed numerically through variables, and the relationships between these variables are being tested and verified using statistical techniques (Bryman and Bell 2011). Hence, quantification in the collection and analysis of data was a necessary step to serve the explanatory purpose pursued by the present research and to aid examination of causal relationships between constructs.

Research Strategy Selection – Archival Research

A research strategy can be defined as a plan of action to achieve project's aims and objectives, and is a methodological tool that bridges the philosophical assumptions with data collection and analysis techniques (Saunders et al. 2012). As such, a carefully designed research strategy guarantees coherence between posed research questions and end goals, and helps address the practicalities of research such as time and resource constraints.

Although the research design strategies are not mutually exclusive, specific scientific paradigms and subject disciplines lend themselves to the use of particular research strategies more than others. So, for example, experiments and surveys tend to be associated with quantitative methodology; ethnography, action research, grounded theory and narrative inquiry with qualitative methodology; while archival research and case studies with the mixed methods approach (Saunders et al. 2012).

Two research design strategies that were considered for the current project were a survey and archival research. Survey is the most widespread strategy in deductive business and management research and is utilised to gather quantitative data for subsequent statistical analysis (Gill and Johnson

1997). Advantages associated with surveys include collection of standardised data to aid comparability, easier and cost-effective access to larger samples, and high level of control over designing research process. Most importantly, surveys allow finding out opinions of the population on specific subject matters. Nonetheless, survey design requires careful sampling and thorough planning of targeted questions and development of accurate instruments to address these questions. Lack of control over the collection process and response rate are recognised as the main challenges associated with the survey research (Bryman and Bell 2011).

Archival research, on the other hand, uses secondary data from existing documents and records as the primary information source. One of the key strengths of archival research is that data depict a high level of objective reality because they were collected for administrative and not research purposes in the first place (Saunders et al. 2012). As a result, it helps investigate events retrospectively and how they change over time. However, it is inevitable that archival research is constrained by the nature and availability of public information sources and secondary data. Therefore, boundaries need to be established early on to find out what type of questions and topics can be answered by accessing specific public data sources. Despite some of its limitations, archival research was chosen as the most appropriate strategy for investigating the development of events as it allows gaining powerful insights from a prolonged time horizon of data.

Data Selection – Secondary Longitudinal Data

The emergence of technologies, Internet and freedom of information legislation created a shift in how data are collected and stored, which facilitated the spread of and access to data, and offered new avenues of potential data sources to social scientists. As a result, there has a been an increased appreciation that secondary sources need to be exhausted before embarking on any primary data gathering (Ghauri and Gronhaug 2002). Increasingly, many governmental, commercial and academic institutions are willing to share their detailed sets of data with the wider public. Such datasets eliminate the need for collection of primary data and allow to investigate wholly or in part a range of research topics. In particular, governmental databases, dedicated data archives, companies' websites and social networking platforms allow open access to rich data.

Secondary data can be both quantitative and qualitative, coming in its raw or compiled form. Social scientists tend to classify secondary data into documentary, survey and multi-source categories (Saunders et al. 2012). Documentary secondary data include textual, multimedia and visual material from companies' internal databases, as well as web and press sources, while survey-based secondary data included censuses and questionnaires of public and private research bodies. Multi-source secondary data refer to sources that compile databases and listings on a broad range of information and material types.

One of the key advantages offered by multi-source secondary data is that quite often it is of longitudinal nature. It was recognised that because time is a crucial dimension of everyday life, understanding how organisational processes occur and unfold over time is of practical and applied significance to researchers (Dansereau and Yammarino 2003 p.313). As Pettigrew (1990 p.269) emphasised, longitudinal research design is *"contextualist and processual in nature"* and *"draws on phenomena at vertical and horizontal levels of analysis and the interconnections between those levels through time"*.

As a result, multi-source data was deemed most appropriate for present research purposes as it allows access to historical data collected over an extended period of time and hence research can be conducted from a 'diary' perspective (Saunders et al. 2012). Also, use of secondary data saves time resources as it eliminates the need to collect primary data and offers particularly extensive insights into research projects that require national and international comparisons. Financial benefits can also be achieved—while some databases may charge a subscription fee, others may be completely free. Moreover, projects conducted using secondary data are believed to conform with research integrity and transparency standards because all datasets can be easily accessed by anyone so that the study can be replicated with ease. Finally, the use of secondary data allows to step away from a pre-defined conceptual framework and explore the patterns in the data that can uncover unanticipated relationships, which normally go unnoticed in survey research which forces answers to a number of specific questions.

One of the major drawbacks associated with using secondary data relates to thoroughness and suitability of methodology with which original data was gathered (Ghauri and Gronhaug 2002). The researcher has limited means of assuring that the data provider adhered to robust collection and analysis standards and that data in the database are accurate and representative. Additionally, some data may prove unsuitable for research purposes due to higher-level aggregations and definitions inconsistent with the ones adopted by the project.

In fact, research design followed in the present project can be more accurately described as multi-source data gathering of relevant information from multi-source databases and listings. That is to say, secondary data were collected by the researcher from a range of secondary multi-source databases and then compiled in a single dataset. Availability of relevant secondary data to answer the research questions of the current project, as well as the breadth of potential sources was established by consulting literature in strategic management and marketing fields that used secondary data in the past. Additionally, library resources were thoroughly investigated to locate relevant datasets and finally, Google search was utilised to find useful sources information using specific search terms.

Measurement Approach – Multi-level

Another important aspect in devising a research methodology is related to the concept level, which refers to the primary unit of measurement and analysis (Bryman and Bell 2011 p.67). Given that the choice of research design is a link between the conceptual and empirical levels (Ghauri and Gronhaug 2002), data measurement approach has to address the multi-level theoretical framework proposed in the present project.

Multi-level research is an important and widely accepted approach to investigating organisational issues. This perspective increasingly dominates the positivist research, which treats multi-level phenomena as occurring in organisations naturally and independently of any observers. These levels are stable and legitimate elements, which, despite having their own standalone existence, are also hierarchically nested (Heracleous and Jacobs 2008). Hence, individuals comprise groups that make up organisations which then form industries, and 'scientific' knowledge is gained by understanding interactions that occur between these levels (Heracleous and Jacobs 2008). Traditionally, the multi-level approach has been concerned with creating a link between micro- and macro-level organisational phenomena (Mossholder and Bedeian 1983; Staw et al. 1981). Micro-perspective includes individual and group-level effects, while macro-level perspective is concerned with wider institutional and economic environment such as strategy and industry dynamics, and the dominant assumption is that organisations function at more than one level (Heracleous and Jacobs 2008).

A primary goal of multi-level research has been to advance the theoretical, conceptual and methodological treatment of data through making statistical inferences from low and high levels of analysis (Rousseau 1985). In this context, methodological consistency can be achieved by specifying a priori levels of constructs, model, and sample, and by using statistical tests to analyse distinct level effects (Klein and Kozlowski 2000). Under this view, sampling and statistical analysis are devised in line with how the level of a theoretical construct fits the conceptual framework (Heracleous and Jacobs 2008). To reflect the latter, the stages of data collection and measurement of variables incorporated the multi-level nature of the theoretical model and data were generated at individual-, project-, firm- and industry-levels. Hence, the first two levels present the micro-perspective, while the latter two levels present the macro-perspective of the organisational phenomena.

Research Ethics

Light touch review mandated by the Ethics Research Framework of the Economic and Social Research Council (ESRC) was undertaken using a pre-defined checklist to estimate the level of potential risk to studied subjects. It was concluded that datasets employed were uncontroversial, and data collected were not sensitive, which indicated no further ethical implications (approved Ethics Form can be found in Appendix 2). Additionally, because the present project utilised publicly available data that anyone has open and unlimited access to, full ethical approval procedure was unnecessary. Nevertheless, current research was conducted under the strict ethical principles and with adherence to a professional code of conduct and Data Protection Act as to respect to studied subjects' privacy. The general ethical considerations concerned avoidance of intentional embarrassment, pain, harm, breach of privacy or any other disadvantage to the subjects studied here (Saunders et al. 2012; Churchill and Iacobucci 2002). As a result, no names or identities of firms or individuals, nor any other personally identifiable information were disclosed or used for purposes other than empirical scientific investigation.

Present research is conducted with a clear understanding that no research methodology can guarantee absolute findings. Instead, care was taken to devise such a research strategy as to minimise room for potential error and obtain tentative and qualified results. The quality of research was sought by maintaining integrity and objectivity during data collection and analysis, and by abiding by 'scientific canons of inquiry'—namely, reliability and validity principles (Saunders et al. 2012). Reliability is concerned with consistency and replicability, and calls for methodological rigour, attention to detail, sound logic, as well as open disclosure of steps followed. Validity is the second element of research quality and relates to the accuracy of operationalisation and measurement of constructs, determination of sound causal relationships between variables, and generalisability to other relevant contexts. The issue of reliability was addressed by devising and following a strict research protocol, which documented every step that was taken during data gathering and data analysis stages. Validity was controlled for through a thorough review of the peer-reviewed literature to compile a list of measures and operationalisations that could be adopted for the purposes of the present project. After, measures extracted from prior literature were mapped over conceptual definitions of constructs used in the model to determine which ones help answer the research questions better.

5.4 Database Development

Empirical Setting

The previous section described the chosen elements of research design that best reflect the researcher's overarching philosophical principles and help to answer the questions posed in this study. This section outlines how the target population was identified and how the sample frame was selected.

Target Population – Database Consideration and Selection

An important and overriding condition for primary database selection was that data were available: (i) on pre-commercialisation activities, (ii) at project-level, (iii) by the phase of development. Also, it was a requirement that the chosen database could be supplemented with additional public sources.

Additionally, given the research focus, projects had to be funded by external sources. Databases containing venture capital deals have been ruled out because they tend to include information at the aggregated firm level, while the aim was to obtain data at the project level. For this reason, databases containing government-funded R&D and innovation projects were deemed the most suitable target population.

A number of government initiatives have been discovered and further investigations identified three potential databases: SBIR & STTR programme in the United States, SMART programme in the United Kingdom and Eurostars-Eureka programme in the European Union. These databases matched the following main criteria:

1. They provided data on separate phases of project development, such as proof-of-concept, concept development and commercialisation.
2. The projects under development followed clearly defined phases that characterise a structured process (e.g. Stage-Gate process of Cooper (2008)) in many respects.
3. Data on projects were well documented at all stages, were reliable and reflected transparent processes.

However, after a careful assessment of the costs and benefits of potential databases summarised in Table 5-2, it was decided that the Small Business Innovation Research (SBIR) database is the most suitable option because it allows to follow projects through phases, offers a longitudinal dataset, and the disadvantages associated with its use are minimal and can be overcome.

Table 5-2: Comparison of potential databases

Database	Advantages	Limitations
Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) programme, US-based	• Phases: I and II • Timeframe: 1983-present • Additional sources of information available	• Sample is limited to small private US-based firms which do not have to file financial information • Phase III is not captured in the database
SMART programme of the Technology Strategy Board, UK-based	• Phases: proof of market, proof of concept, prototype development • Timeframe: 2011-present	• Projects do not follow through phases consecutively • Insufficient data on projects that went through one phase to another • No data on project outcomes
Eurostars-Eureka programme, EU-based	• Phases: complete, withdrawn, running, on hold, not started • Timeframe: 2007-present • International projects led by R&D performing SMEs	• Complicated network of participants • Not enough on data on unsuccessfully completed or terminated projects • Limited additional data sources

Source: Author's analysis of SBIR, SMART and EUROSTARS online platforms

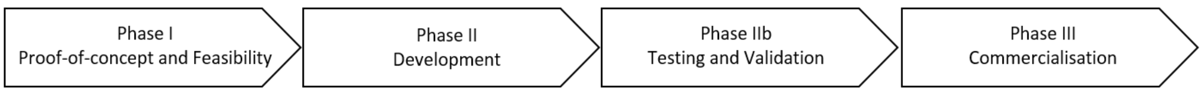
The SBIR initiative is administered through the U.S. Small Business Administration (SBA) and is funded by one of the eleven Federal Agencies. The programme is structured in three phases and aims to fuel the growth of the U.S. economy by encouraging small businesses to explore their entrepreneurial and technological potential, stimulating commercialisation of the technology, product, or service spurring from R&D and innovation activities. All proposals are peer-reviewed and awards are granted on a competitive basis based on scientific and technical merit and commercial potential (SBIR 2015). Table 5-3 presents a summary of the main elements of the SBIR programme and Figure 5-3 depicts a sequence of phases followed by the initiative. The scope of the current study only includes projects that participated in Phase I and Phase II of the programme.

Table 5-3: Summary of the main elements of the SBIR programme

Programme Element	Description
Objectives	• Stimulate technological innovation; • Meet federal research and development needs; • Increase private sector commercialisation of innovations developed through federal R&D funding; • Foster and encourage participation in innovation and entrepreneurship by socially and economically disadvantaged persons and women-owned small businesses.
Eligibility criteria	• Qualify as Small Business Concern; • Have not more than 500 employees; • Be organised for profit and have a legal company form; • Operate primarily within the U.S.; • Be more than 50% owned by and controlled by one or more citizens of the U.S.
Three-Phase Programme	**Phase I - Feasibility and Proof of Concept:** • Objective: establish the technical merit, feasibility, and commercial potential of the proposed R/R&D efforts and determine the quality of performance of the small business organisation prior to providing Phase II award; • Budget: up to $150,000 per project; • Duration: 6 months (SBIR) to 1 year (STTR); **Phase II - Research/Research and Development:** • Objective: continue the R&D efforts initiated in Phase I. Funding is based on the results achieved in Phase I and the scientific and technical merit and commercial potential of the project proposed in Phase II. Only Phase I awardees are eligible for a Phase II award; • Budget: up to $1 million per project; • Duration: up to 2 years. **Phase IIB - Bridge Award:** • Objective: address the funding gap between the end of the SBIR Phase II award and the subsequent round of financing needed to advance a product or service toward commercialisation. The Bridge Award is designed to incentivise partnerships between SBIR Phase II awardees and third-party investors and/or strategic partners; • Budget: up to $1 million per project per year; • Duration: up to 3 years. **Phase III - Commercialisation:** • Objective: pursue commercialisation objectives resulting from the Phase I & II; • Budget: the SBIR/STTR programs do not fund Phase III.

Source: SBIR

Figure 5-3: Phases of the U.S. SBIR/STTR programme



Source: SBIR

Figure 5-3 shows that the SBIR initiative stipulates clearly defined phases of a structured process. Appendix 3 presents a schemata which shows how the SBIR programme maps onto different new project development models.

Sample Frame – Agency Consideration

Having selected the most suitable database to address the research needs, the next stage was to limit the number of cases in the population by clusters contained within the sample frame (Saunders et al. 2012 p.262).

As a first step of the sampling procedure, to reduce the heterogeneity among projects in the sample frame, it was necessary to choose one of eleven participating federal agencies[18].

Table 5-4: Top five SBIR/STTR programme funding federal agencies – 2012 performance

Federal Agency	Total Awards (million $)		Success Rate		Cost per Project ('000 $)		Cost per Project (2006-12 % CAGR)	
	Phase I	Phase II	Phase I	Phase II	Phase I	Phase II	Phase I	Phase II
DOD	237.5	573.7	19%	73%	120.3	413.9	5.1%	-7.3%
HHS	217.1	244.9	18%	48%	227.8	765.4	4.9%	-5.1%
DOE	66.9	145.2	16%	43%	180.8	1,009.9	10.2%	9.8%
NASA	36.8	71.4	16%	21%	123.3	728.5	9.2%	3.7%
NSF	35.4	65.4	11%	43%	147.5	480.8	7.1%	-7.7%
Total of 11	**613.3**	**1,139.7**	**17%**	**56%**	**152.6**	**530.1**	**5.9%**	**-4.9%**

Note: Success rate is calculated as the ratio of the number awards granted to the number of applications received.

Source: SBIR 2006-2012 annual reports, author's analysis

First, top five agencies were selected by size and then further narrowed down by their propensity to fund projects that are high-tech and have a strong incentive to commercialise. Having examined objectives and portfolios of the agencies, the National Science Foundation (NSF) and the National Institutes of Health (NIH) of the Department of Health and Human Services (HHS) were identified as the most relevant for the research project.

Next, a pilot study was conducted to establish the feasibility of data gathering execution task from secondary sources. To assess the level of difficulty of retrieving relevant information, five SBIR-funded projects were selected from each of two agencies and data were collected on a number of set dimensions. Further to this exercise, it was concluded that the NIH offers a more sophisticated and easy-to-navigate repository of SBIR-funded projects, Research Portfolio Online Reporting Tools (RePORT), and the nature of firms participating in the scheme allows supplementing the main database with reliable additional sources.

As a second step of the sampling procedure, the sample frame was further narrowed down by clusters that make up the NIH. The NIH comprises 27 institutes and centres, each with focused

[18] Eleven agencies participating in the SBIR / STTR programme are: Department of Agriculture (NIFA), Department of Commerce (NIST & NOAA), Department of Defense (DOD), Department of Education (ED/IES), Department of Energy (DOE), Department of Health and Human Services (HHS), Department of Homeland Security (DHS), Department of Transportation (DOT), Environmental Protection Agency (EPA), National Aeronautics and Space Administration (NASA), and National Science Foundation (NSF).

research agenda on specific diseases (NIH 2015). For the purpose of this study, the sample was limited to the projects funded by the National Cancer Institute (NCI) because (i) it is the second largest funder in terms of the number of projects and total budget; (ii) projects have the lowest success rate, although the total cost per project has increased by 4.6% compound annual growth rate (CAGR) in the period 2008-12, as demonstrated in Table 5-5.

Table 5-5: Top five SBIR/STTR programme funding NIH institutes[19] – 2012 performance

Institutes and Centers	**Total Awards (million $)**		**Total Awards**	**Success Rate**	**Cost per Project ('000 $)**		**Cost per Project (2006-12 % CAGR)**	
	Phase I	Phase II	Phase I&II	Phase I&II	Phase I	Phase II	Phase I	Phase II
NIAID	44.1	73.6	254	20%	272.0	855.5	8.8%	7.4%
NCI	24.0	47.5	190	12%	220.0	709.5	4.6%	4.6%
NHLBI	23.8	43.9	167	21%	264.3	719.3	-2.7%	-2.0%
NIGMS	20.2	36.5	168	24%	222.0	588.6	3.7%	0.6%
NIDDK	13.0	33.7	100	14%	289.8	701.5	12.0%	8.7%
Total of 27	**217.0**	**411.9**	**1,668**	**19%**	**235.4**	**653.7**	**4.8%**	**4.1%**

Note: Success rate is calculated as the ratio of the number awards granted by the number of applications received.

Source: NIH report, author's analysis

Although oncology research has evolved separately yet in parallel with drug development technological platforms (Sosa 2009), it forms the basis for the market of anticancer drugs and treatments, and there is a prominent link between research competence, product quality and resulting firm profitability (Lu and Comanor 1998). The latter characteristic was important given that the present study focuses on the connection between R&D and commercialisation activities.

Sampling

The current section describes the sampling strategy followed to arrive at the final sample used in the analysis. The sample is based on all Phase I and Phase II projects that were funded under the SBIR/STTR programme between 2006 and 2012. The choice of the timeframe was driven by the fact that to be able to obtain supplementary information from the secondary sources, the projects studied had to be relatively recent. Hence, it was decided that the time horizon of seven years was deemed sufficient for current research purposes.

First, two separate lists of participants were retrieved—one containing all awards by the HHS from the SBIR database and another by the NCI from the RePORTER database of the NIH. Neither

[19] Top five SBIR/STTR programme funding NIH institutes are: National Cancer Institute (NCI); National Institute of Allergy and Infectious Diseases (NIAID); National Institute of General Medical Sciences (NIGMS); National Heart, Lung, and Blood Institute (NHLBI); National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK).

database was an ideal choice: while the SBIR database only allowed limiting the search by the funding federal agency (i.e. HHS) and not by the funding institution (i.e. NCI), NIH RePORTER database had some missing information and awards were not clearly reported by funding phase. As a result, it was decided to cross-check the SBIR list of projects against the NIH Reporter database to make sure that only NCI-funded projects get included and then merge both databases by matching project titles in order to compile one exhaustive dataset.

In line with one of the primary research objectives to examine the effects of funding continuation, the next step was to code all Phase I projects according to whether they proceeded to Phase II or not. To do that, the dataset was screened to find matching Phase I - Phase II pairs of projects. Discontinuation of Phase I was coded as 1 and continuation of Phase I was coded as 0. If the Phase I project did not have a corresponding Phase II project in the dataset within four years[20] of Phase I award receipt date, it was coded as discontinuation.

As Table 5-6 shows, it was possible to classify 72% of projects from the initial database of 3,006 projects funded by the NCI in the period 2006-2012. Of these, 72% were Phase I projects and 28% Phase II projects. The coding procedure revealed that the success rate of Phase I projects in the given timeframe was 22%, while the non-progression rate was at 78%.

Table 5-6: Overview of the initially retrieved sample before and after coding procedure

Stage		**Count**	**%**
Before coding	Number of Phase I projects	2,171	72%
	Number of Phase II projects	834	28%
	Total number of Phase I and II projects	**3,006**	**100%**
After coding	Projects classified as ‘proceed to Phase II’	491	22%
	Projects classified as ‘do not proceed to Phase II’	1,668	78%
	Total number of classified projects	**2,159**	**100% (72% of all projects)**

To accommodate the unequal occurrence rates of projects with progression versus non-progression to Phase II, it was decided that the current research would benefit from a sample of relatively equal number of projects that proceeded to the second stage of funding and the ones that did not.

[20] According to sbir.gov, duration of a typical Phase I SBIR project is 6 months, and 12 months of the STTR project. All proposals for Phase II have to be submitted within 6 receipt dates (21 months), while decisions on whether or not the project will receive Phase II award take up to 9 months to make. So, the usual leeway between Phase I award and successful Phase II is 3 years for SBIR awards and 3.5 years for STTR awards, which was increased to 4 years to ensure accuracy of the coding procedure.

The aim was to have a sample of 383 observations because statistically such size presents characteristics of the population of 100,000 cases at 95% confidence level[21] (Saunders et al. 2012 p.266). The projects were randomly selected using the 'rand' function in Excel, which generated a sample of 383 projects, of which 186 were 'continue' cases and 197 'discontinue' cases.

Data Generation

As has been described in the earlier section, multi-level measurement approach was adopted and implemented at the data generation stage. Multi-level data generation approach refers to the case when predictors are measured at more than one level of aggregation (Cohen et al. 2003).

Therefore, data were collected on three levels of characteristics relevant to the current research project—project-level characteristics, individual-level characteristics and firm-level characteristics.

Project-level Characteristics

All project-level data were collected on Phase I awards because of truncation of projects non-continuing to Phase II, for which no information was available. SBIR and NIH databases were used to compile a primary dataset, from which meaningful information related to projects was coded as dummies and categories, and abstracts describing projects were analysed. In addition to collecting data on the individual project level, data on firms' projects were also collected at the portfolio level in order to investigate aggregated effects of prior funding.

Individual-level Characteristics

Individual-level characteristics capture two important units of analysis—manager and principal investigator. The manager was defined as the person whose name appears in the database as the 'main contact', while the principal investigator is the scientist responsible for the execution of the project. Data provided by the SBIR and NIH databases were used as a starting point to get a list of individuals' names and then supplemented by a number of other publicly available secondary data sources.

LinkedIn was employed to collect data on social capital characteristics for the individual-level analysis. LinkedIn is the world's largest professional network consisting of more than 400 million members in over 200 countries, and intends to stimulate information exchange among its members, by requesting to share current and past educational and employment background, location,

[21] For the population of 2,000 cases, which is representative of the current study, the sample size could be safely reduced to 322 observations.

professional interests, news, and other relevant information. The LinkedIn social media platform is used by organisations as a marketing, recruitment, PR, analytical and networking tool, which make the website not only a legitimate but also a high-involvement setting for business professionals (Mintz and Currim 2013).

Apart from being used to post study invitations and solicit surveys (Cholakova and Clarysse 2015; Butts et al. 2015), LinkedIn has gained popularity in recent years in business research as a reliable secondary source to collect data on people’s biographies, including educational background and work experience (Gomulya and Boeker 2014; Byrne and Shepherd 2015; Dokko and Gaba 2012; Reyt and Wiesenfeld 2015) and social network connections (Colombo et al. 2015). A search of LinkedIn was conducted based on the person’s name along with the company’s name to make sure that profiles of the right individuals were located and retrieved for further analysis. LinkedIn profiles were also supplemented by biographies published on companies’ websites.

When a person did not have a LinkedIn profile or it was incomplete, following Gomulya and Boeker (2014) and Graffin et al. (2013), several additional websites were used that list information on the companies and their employees, including ZoomInfo and Bloomberg Business Week. For completeness, the search was also conducted via Google engine by entering the name of the company along with the name of the individual in question and screening the first five pages of returned results to complete data gathering effort on educational background and work experience. Altogether, the data collection task has been exercised with the thorough attention which indicates a high degree of data reliability and comprehensiveness.

Also, Elsevier’s Scopus database of peer-reviewed literature was used to collect data on individuals’ academic performance as assessed by publications and citations from journals, books and conference proceedings. Scopus was chosen over Web of Science because it has an author identification tool which helps locate the right people, covers the majority of scientific journals and has an easy to navigate interface. Authors were searched by name, and once the right person was located, information was retrieved from the profile, such as the number of publications total and by type, as well as citations, self-citations and h-index.

Firm-level Characteristics

Firm-level data gathering was focused on firms’ attributes such as size, age, business activity and patenting activity.

Participants of the SBIR programme are small private firms, so obtaining data on firm size was a major challenge because in the United States such firms are not legally required to report their financial performance. Therefore, it was not possible to collect data on firm size from conventional databases such as COMPUSTAT or EDGAR database of the U.S. Securities and Exchange Commission (SEC). Instead, Hoover's Online database, which covers small and private companies, was utilised to capture the most recently reported figures on sales and number of employees, as well industry codes. Hoover's database has been extensively used in prior research, particularly in the marketing field, to obtain objective data on small private firms (Aboulnasr et al. 2008; Boyd et al. 2010; Cui and O'Connor 2012; Dotzel et al. 2013; Morgan and Rego 2009; Rego et al. 2013; Vorhies et al. 2010). If the company was not reported in the Hoover's database, several additional websites were used beyond the focused Hoover's searches such as ZoomInfo, Manta, Find the Company, SalesSpider, PrivCo and CorporationWiki.

PatBase database was used as the primary source to collect data on firm's patenting activity, including patent applications and publications of firms and individuals, but also to analyse patents in detail, reporting data on patent classes, invention team, countries and claims. PatBase is an online comprehensive patent database, and apart from having wide global coverage, it offers such advantages as convenient navigation of the search engine and a sophisticated analysis tool. When information on PatBase was unavailable or incomplete, Espacenet database of the European Patent Office (EPO) was used as a complimentary resource.

5.5 Operationalisation and Measurement of Constructs

Performance Measures

As described in Chapter 4, outcomes of investment were conceptualised from two perspectives—investors' and firms'. Accordingly, the measures of performance were structured in line with objectives pursued by the SBIR investment programme; that is, increase commercialisation, encourage entrepreneurship and stimulate innovation, which in current research are equated to post-funding sales performance, employment creation and innovation activity, respectively. Subsequently, measures of absolute performance were used to reflect the firms' perspective and measures of yield on investment were used to reflect the funders' perspective. Prior research found empirical evidence in support of two indicators of venture performance, namely growth and business volume, which offer advantages such as good availability, internal consistency, relative objectivity and content validity (Chandler and Hanks 1993). The measure of growth tends to be captured in terms of change in market share, cash flow and sales; while business volume is typically expressed as earnings, sales and net worth (Chandler and Hanks 1993).

There is a consensus that sales are the most favoured indicator of growth and financial performance of firms (e.g. Hoy et al. 1992). First, the measure of sales applies to the majority of businesses (Davidsson and Wiklund 2000). Second, it is relatively capital insensitive (Delmar et al.

2003). Third, it is a result of firms' natural evolutionary processes (Delmar 1997). And finally, it is an indicator of market acceptance of a venture's commercialisation efforts (Clarysse et al. 2011). However, the measure of sales suffers from market fluctuations and also there may be an indefinite time lapse until the firms start to realise sales from any start-up of new activities (Delmar et al. 2003). Hence, it is crucial to also evaluate the ventures' performance on a non-financial basis (Clarysse et al. 2011).

The indicator that is immune to the limitations of the sales measure is that of employment. Employment better captures organisational complexity (Churchill and Lewis 1983), which is directly linked to the resource-based view of the firms (Kogut and Zander 1992). Moreover, the accumulation of employees has both managerial and macroeconomic implications, being related to venture growth (Chandler and Hanks 1993) and job creation (Picot and Dupuy 1998) respectively. In the high technology sectors, growing rate of employment is an indicator of the value of a start-up (Davila et al. 2003) and a signal of better access to new and control of existing capabilities (Guedj and Scharfstein 2004). However, it has been noted that a firm can realise efficiency-related gains in production output and capital without having to increase its stock of personnel (Delmar et al. 2003).

To overcome this potential drawback, the study introduces the third dimension of firm's performance—innovation activity. The notion of differential inventiveness has been linked in the economic literature to sources of economic growth, the rate of technological change, the competitive position of different firms and countries, and dynamics of alternative industries (Griliches 1990). Because there are no direct measures to capture any of the aspects related to inventiveness, patent statistics have been recognised as an objective and widely available proxy (Griliches 1990). Findings of prior studies indicate a strong, nearly proportional relationship between R&D expenditures and a number of patents, implying heterogeneity in inventive activity across firms; and such pattern is especially prevalent among firms of smaller size (Griliches 1990). Additionally, empirical evidence exists that there is a positive association between firm's patent stock and new product development outcomes (McMillan et al. 2003). Given that one of the objectives of the present research is to analyse whether additional R&D awards lead to improvements in commercialisation performance, patent statistics present an important metric.

Consistent with prior work in organisational studies (Benner and Waldfogel 2008; Benner and Tushman 2002; Rosenkopf and Nerkar 2001), patent data measured innovative and inventive activity. R&D investments generate knowledge output in the form of patent applications, which after some time are published and then knowledge they contain becomes available for use by the wider public (Ramani et al. 2008). Therefore, patenting is seen as the first step towards commercialisation (McGrath and Nerkar 2004).

Taking into account the timing issues of the patenting process, prior research tends to differentiate between patent publications and grants on the one hand, and patent applications on the other hand. The number of patent applications is arguably an indicator of inventive activity because it is the first statement of new knowledge (Hsu and Ziedonis 2013). In contrast, the number of patent publications and grants is a better indicator of innovative activity and technological base (Hsu 2007; Zucker et al. 2002) and its availability to public domain makes it possible to assess the value of new knowledge through the number of citations (Deeds et al. 1997). Nevertheless, such distinction is rather ambiguous in empirical studies and researchers use both patent applications and publications interchangeably to refer to both inventive and innovative activity. Therefore, for current purposes, patent applications were used throughout the study except when the measure needed to be quality-adjusted, patent publications and their citations were used. In line with previous literature, the flow of recent patent applications was used to proxy inventive productivity (Hsu and Ziedonis 2013; Haeussler et al. 2014; Heeley et al. 2007).

To sum up, the current project focuses on sales, employment and innovation because the following measures are the most widely used in empirical growth research (Delmar et al. 2003) and entrepreneurship literature (Murphy et al. 1996; Sobel 2008; Gartner and Shane 1995). Also, these indicators are the only ones available in the present study for all of the firms of interest.

Absolute Performance

Following the logic explained in the previous paragraph, sales performance was measured as the firm's revenue in million dollars in t_{2014}; employment performance was measured as the number of people employed by the firm in t_{2014}; and innovation performance was measured as the cumulative count of firm's patent applications since the project award year, that is, in the period from t until t_{2014}.

$$Sales\ Performance = Sales_{t_{2014}}$$

$$Employment\ Performance = Employees_{t_{2014}}$$

$$Innovation\ Performance = Patent\ Applications\ _{t,t+1,\ldots t_{2014}}$$

It can be acknowledged that absolute performance variables may also be indicators of organisational size and organisational resources, and, given the theoretical objective of this project, which is to focus more on the evolutionary dynamics of change than on a complete and detailed representation of a firms' operational performance, selection of such measures was purposeful (Zott 2003).

Yield on Investment

The rate of return on investment (ROI) is a fundamental concept used for financial efficiency evaluation of a single investment project or of a number of projects, and is most commonly expressed as the gain-to-cost ratio:

$$ROI = \frac{(Gain\ from\ Investment - Cost\ of\ Investment)}{Cost\ of\ Investemnt}$$

The logic of the ROI is further narrowed down to the notion of yield on the government investment, conventionally measured as the change in the social value of a unit of private sector firm's performance from an investment which takes place in the following period (Bradford 1975). Such change is operationalised as a one-period rate of return r_t from t to t_{2014}.

$$Sales\ Yield = \frac{Sales_{t_{2014}}}{\sum_{t,t-1\ldots t-n} Total\ Prior\ Investment}$$

$$Employment\ Yield = \frac{Employees_{t_{2014}}}{\sum_{t,t-1\ldots t-n} Total\ Prior\ Investment}$$

$$Innovation\ Yield = \frac{Patent\ Applications\ _{t,t+1,\ldots t_{2014}}}{\sum_{t,t-1\ldots t-n} Total\ Prior\ Investment}$$

where total prior investment refers to the cumulative dollar amount received for all prior SBIR / STTR grants.

Historical sales and employment figures for year *t* were not available in the Hoover's or any other known database, indicating that the measures of sales and employment yield could be overstated. Since only the closing sales and employment figures were known, it was not possible to calculate the change for the period, resulting in the maximum yield measure. The 100%-growth yield measure was included in the main analysis and is, in fact, the best yield that the funders could possibly achieve. It means that the relationships between independent variables and 100%-growth yield measures would depict the strongest possible association.

Although the assumption that the sales and employment have grown by 100% since year t may be correct given that many funded firms are start-ups, to make sure that the results were not affected by the limitation of data availability, the value maximisation criterion was extrapolated and used to perform sensitivity checks in the extension analysis. According to Sageworks' Private Company Report (Forbes 2014), small private firms in the U.S. experienced growth of 8.9% in 2012 and 9.6% in 2011. Informed by these statistics, the measures of sales and employment yield were then reduced to a more realistic 10% rate of sales and employment growth. As a result, the sales and employment figure in the opening period was assumed to be 90% of the closing period figure. The measure of innovation activity refers to the number of applied patents after project start and hence, represents a change in patent applications stock since year *t*, which indicates that the measure did not suffer from possible overstatement and did not merit inclusion in the sensitivity analysis.

Real Options Reasoning Elements

Initial Commitment

Initial funding commitment refers to the resource allocation at the point of investment decision. In the current context, it was examined from two angles—single project and cumulated portfolio.

Initial commitment at the individual project level was operationalised as the dollar amount of Phase I award granted to an individual project in the database. Initial commitment at the cumulated portfolio level was operationalised as the average dollar amount the firm received across all prior Phase I awards funded under the scheme. The figures of financial value and count of Phase I awards were retrieved from the SBIR database.

Both variables were measured on a continuous scale to test the expectation proposed in the hypotheses that the higher is initial funding commitment, the higher is the negative effect on desired outcomes of the ROR investment logic. Consistent with Klingebiel and Adner (2015), for robustness checks only, initial commitment was also measured on a binary scale, whereby low initial commitment was coded as 1 when values lied below the mean value of initial commitment of the sample and high initial commitment was coded as 0 when values were equal to or above the mean value of initial commitment.

Discontinuation

Funding discontinuation reflects a propensity to reallocate resources from less promising projects to guarantee financial flow to projects with higher potential (Klingebiel and Adner 2015). Funding discontinuation was measured at the individual project level and operationalised as a binary variable, i.e. whether or not Phase I project received subsequent Phase II funding. The dummy variable was coded as 1 for non-progression from Phase I to Phase and 0 for progression.

Sequencing

Funding sequencing assesses the extent of consecutive allocation of funding resources to projects across stages of development (Klingebiel and Adner 2015). Such measure is fundamental in understanding the dynamics of portfolio-level project interactions (Girotra et al. 2007). It was measured at the cumulated portfolio level as Phase II Transition Rate, which was operationalised as a ratio of a number of previously received Phase II awards per total received Phase I awards. Similar to initial commitment, as an alternative measure for robustness checks, sequencing was also operationalised as a dummy, with low sequencing coded as 1 to include values below the mean value of sequencing of the sample and high sequencing coded as 0 to include values equal to or above the mean value of sequencing.

Fit of Funding Decisions

The fit of funding decisions is designed to measure the consistency of resource allocation decisions and to what extent the elements of the ROR elements match under the overarching logic. That is, real options logic implicitly mandates that efficient funding regimes are the ones where low initial commitment is followed by funding discontinuation and high initial commitment is followed by funding continuation (Adner 2007).

The variable was investigated at both single project and cumulated portfolio levels and was operationalised as an interaction of initial commitment and reallocation. At the single project level, initial commitment was transformed from a continuous to binary scale, whereby low initial commitment category captured values below the mean sample initial commitment, and high initial commitment category captured values including and above the mean initial commitment. Subsequently, fit of funding decisions was coded as Low initial commitment x Discontinue / High initial commitment x Continue and was given a dummy value of 1, while no-fit of funding decisions was coded as Low initial commitment x Continue / High initial commitment x Discontinue, and was given a dummy value of 0.

At the cumulated portfolio level, initial commitment was coded into the low and high category as described above. Then, to capture the propensity to discontinue funding at the portfolio level, Phase II Transition Rate equal to zero was equated to Discontinue, while Phase II Transition Rate above zero was equated to Continue. Fit and no-fit of funding decisions were coded in the same way as the project-level variable: the value of 1 was given to Low average initial commitment x No Sequencing / High average initial commitment x Sequencing, while the value of 0 was given to Low average initial commitment x Sequencing / High average initial commitment x No Sequencing.

Role Legitimacy Signals

Executive's Functional Role

Duality is a term used to signify that one individual occupies two positions (Sanders and Carpenter 1998). Executives' functional role was expressed as their position in the firm. Consistent with prior research (e.g. Boone et al. 2004), position in the firm was measured as a dummy variable of whether the manager and the principal investigator was the CEO (1) or not (0) at the award date.

Organisational Tenure

Longer-tenured TMTs in new firms are perceived to be better equipped to grasp, shape and control processes that improve functional and operational capabilities (Patel and Jayaram 2014). In line with prior studies (Sanders and Carpenter 1998; Hughes et al. 2010; Zhang and Wiersema 2009; Wu et al. 2005; Zhang 2006), tenure in firm was measured on a continuous scale as the total number of years the manager and the principal investigator had been working in the firm at the award date.

Technical Experience

Technical skill is one of the most crucial competences of TMT members (Katz 1982) and denotes the level of experience in different functional roles (Ensley and Hmieleski 2005). Technical experience was operationalised in prior research as a number of years spent in research, development, engineering, and other technical positions (Minola and Giorgino 2008). Following the logic, technical experience was measured on a continuous scale as the total number of years the manager and the principal investigator had served in technical positions in the same sector as the firm before award date.

Entrepreneurial Experience

Prior research has approached the measurement of the concept of entrepreneurial experience from different angles. Kirsch et al. (2009), and Tornikoski and Newbert (2007) operationalised entrepreneurial experience as the total number of past claimed start-up experiences, Wennberg et al. (2011) as the number of prior years, while Minola and Giorgino (2008) used a dummy to code whether the member of the TMT had previous start-up experience or not. The continuous scale was preferred over other alternatives as it allows capturing more information on the studied phenomenon. Hence, entrepreneurial experience was measured on a continuous scale as the total number of years the manager and the principal investigator had accumulated in starting up activities in any sector before award date.

Resource Legitimacy Signals

Elite Education

Elite education refers to the rated prestige of the academic institutions a focal TMT member attended and is a proxy for the status of an educational affiliation (Stern et al. 2008). Elite education has been operationalised as a categorical measure coding whether undergraduate or graduate schools were elite (Haleblian and Finkelstein 1993).

For present purposes, it was decided to concentrate on the latest academic institution that a TMT member attended because it is the most recent in time and hence the most relevant to the evaluation of social capital. Elite education was measured in two steps. First, the name of the latest university the manager and the principal investigator attended was recorded. Then, it was allocated a score from the Top 100 worldwide universities ranking. Universities not in the top 100 received a score of zero. Hence, the present measure of elite education not only differentiates between elite and non-elite schools but also compares elite institutions to each other by using objective scores. Historical data were available, so the scores were applied from the ranking table published in the same year as the Phase I award was announced.

The ranking table was retrieved from the Academic Ranking of World Universities (ARWU) published by Shanghai Ranking Consultancy (Shanghairanking 2013). This source was chosen over the other alternatives, such as the World University Rankings by The Times Higher Education, QS and the U.S. News, because ShanghaiRanking Consultancy is a fully independent organisation on higher education information and is located outside of the United States and Europe, two educational powerhouses, which adds credibility to the source. Additionally, the ARWU, conducted by researchers at the Centre for World-Class Universities of Shanghai Jiao Tong University (CWCU), uses a robust methodology. Over 1000 global universities are ranked on four categories of academic and research performance and scores for each indicator are then weighted to determine the highest scoring institution which is assigned a score of 100, and other institutions are calculated as a percentage of the top score (Figure 5-4). The final league table includes the scores and ranks of the best 500 institutions.

Figure 5-4: Indicators and weights for ARWU

Criteria	Indicator	Code	Weight
Quality of Education	Alumni of an institution winning Nobel Prizes and Fields Medals	Alumni	10%
Quality of Faculty	Staff of an institution winning Nobel Prizes and Fields Medals	Award	20%
	Highly cited researchers in 21 broad subject categories	HiCi	20%
Research Output	Papers published in Nature and Science[22]	N&S	20%
	Papers indexed in Science Citation Index-expanded and Social Science Citation Index	PUB	20%
Per Capita Performance	Per capita academic performance of an institution	PCP	10%
Total			**100%**

Source: Shanghai Ranking

Advanced Business Education

MBA degree was used as a proxy of advanced business education. Education has been frequently operationalised as a dichotomous variable in prior studies (e.g. Tornikoski and Newbert 2007). Similarly, MBA degree was measured as a dummy variable of whether the manager and the principal investigator had an MBA title (1) or not (0).

Advanced Technical Education

Advanced technical education was operationalised in terms of the presence of a doctorate degree. As in previous studies (e.g. Gruber et al. 2013), doctorate degree was measured as a dummy variable of whether the manager and the principal investigator had a doctorate title (1) or not (0). The doctoral title included the PhD and MD degrees.

Academic Seniority

Academic seniority was operationalised in terms of a professorship status. Professorship was measured as a dummy variable of whether the manager and the principal investigator held a professorship position (1) or not (0).

[22] For institutions specialised in humanities and social sciences, the weight of N&S is relocated to other indicators.

Intellectual Legitimacy Signals

Inventive Capacity

The research concluded that individual inventors are valuable to firms (Gruber et al. 2013) because they are effective at recombining existing knowledge from different domains to generate new ideas, inventions and innovations (Glynn 1996; Hargadon and Sutton 1997; Gupta et al. 2006; Taylor and Greve 2006). The inventive output is often used as a proxy to measure the capability to increase the quantity and quality of knowledge stock (Grigoriou and Rothaermel 2014). Inventive capacity demonstrates the ability to translate advances in academic work as well as R&D activities into practical technological applications, creating a scope of innovation opportunities. As a result, such output-based measure can also be used as a proxy for inventor's ability (Conti et al. 2014) and individual-level assimilative capacity (Banerjee and Campbell 2009).

Inventive capacity refers to the breadth and depth of inventors' expertise and experience (Boh et al. 2014) and has been measured by the cumulated stock of patents previously applied for by the inventor (Singh and Fleming 2010; Conti et al. 2014). Following from this, inventive capacity was operationalised as the total number of patent applications the manager and the principal investigator had filed before award date.

Academic Competence

Prior research indicated that both publications and patent productivity are complementary productivity outcomes of individuals in the life-sciences industry (Powell and Owen-Smith 1998). Prior studies used the total number of publications of the scientists as a measure of their research productivity (Bercovitz and Feldman 2008) and as a proxy for scientific reputation (Stern et al. 2008). As a result, academic competence was constructed as the total number of documents the manager and the principal investigator had published before award date. Published documents included journal articles, conference papers, books, and other work, such as meetings, reviews, corrections, clinical trials, editorials, and letters.

Abstract Readability

Readability reflects firms' effectiveness in communicating information relevant to assessing applications for funding (Loughran and McDonald 2014). The Gunning-Fog score, also known as the Fog Index, is often applied in textual analysis to evaluate the extent of document readability and its compliance with the plain English rules (Loughran and McDonald 2014). Other commonly used readability measures are the Flesch–Kincaid measure, the Flesch Reading Ease Score, Coleman-Liau

Index and McLaughlin's SMOG Index. As opposed to the Fog Index, which is built upon a binary classification of complex words (i.e. more or less than two syllables) (Gunning 1952), both Flesch measures use an exact count of syllables in their readability formulas (Flesch 1948). In addition, while the Fog Index and Flesch Reading Ease Score create numeric estimates, the Flesch–Kincaid measure produces scores on a scale from 0 to 100. On the other hand, the SMOG Index estimates the number of years in education needed to comprehend a piece of written text and counts the number of polysyllables (words of three or more syllables) in three samples of ten sentences (McLaughlin 1969).

Unlike other measures, Coleman-Liau Index measures word length in characters rather than syllables, which enables easier calculation using devices to scan hard-copy text instead of electronic text on computers (Coleman and Liau 1975).

Although all alternatives are evidently very similar, the Fog Index was employed in this study because this measure is more widespread and more often used in finance and accounting literature (F. Li 2008; Biddle et al. 2009; Lehavy et al. 2011; Lawrence 2013; Loughran and McDonald 2014).

The Gunning-Fog readability measure was adopted to evaluate the complexity of the abstract provided in the Phase I project application and the scores were obtained using an online calculator (ReadabilityScore 2015) which utilises the following formula:

$$Gunning - Fog\ Score = 0.4 \times (average\ number\ of\ words\ per\ sentence + percent\ of\ complex\ words)$$

where average words per sentence refers to the number of words in the abstract divided by the total number of sentence termination characters; percent of complex words refers to the percentage of words with more than two syllables. Higher values of the Fog Index imply less readable text.

Efficacy Signals

Post-funding Project Duration

Speed is an important concept in assessing organisational problem-solving ability and efficiency, and it refers to how quickly the firm can transition a product or project from one stage of development to another (Chandy et al. 2006). Hereby, project duration was measured as the total length of time taken to complete the Phase I of the project and was operationalised as the number of days elapsed between Phase I project start and end date.

Post-funding Invention Activity

Consistent with the logic adopted in the section describing performance measures, invention activity was evaluated as firm's propensity to apply for patents. Post-funding invention activity was operationalised as the number of patent applications a firm filed in a 3-year window following a Phase

I award. A window of 3 years reflects the average time between Phase I and Phase II commencement, and hence is a proxy for firm's efficiency to exploit funds to convert ideas into patentable innovations. The measure is in line with other studies in the venture capital context. For example, Guler (2007) calculated the number of acquired patents between the first and final investment rounds to infer the progress of the firm in the funding process.

Project Appeal Characteristics

Project Scope

It was suggested that product scope is more than an indication of an extent of firm's product portfolio diversification, and also signifies the breadth of expertise and depth of knowledge that evolve as a result of engagement in multiple innovation domains (Sorescu et al. 2003).

In the present research, project scope refers to the breadth of initial application for funding and was operationalised as whether a project targets a specific cancer type or multiple cancer types. The broad scope was coded as 1 when a project targeted multiple cancer types, while the narrow scope was coded as 0 when a project targeted a specific cancer type. To assign a project into the relevant category, description of cancer types being targeted was derived from abstracts of projects.

Project Category

Project category refers to the type of the federal programme that the project is assigned under the SBIR initiative, as outlined in the Catalogue of Federal Domestic Assistance (CFDA). CFDA categories were coded as follows: Cancer Cause and Prevention Research was coded as 1, Cancer Detection and Diagnosis Research was coded as 2, Cancer Treatment Research was coded as 3, Cancer Biology Research was coded as 4.

Capabilities

There is a stream of literature that has inferred superior firms' capabilities from a sustained superior performance by investigating how heterogeneity in unique capabilities and routines that are hard to imitate drives heterogeneity in performance which subsequently leads to sustained competitive advantage (Winter 1971; Lippman and Rumelt 1982; Levinthal 1997). However, there has been criticism that such view of capabilities may be theoretically and empirically tautological, whereby superior capabilities may not necessarily be an indicating prerequisite of observed superior performance (Powell 2001; Priem and Butler 2001; Durand 2002; Denrell 2005; Durand and Vaara 2009;). Another group of researchers proposed that superior competitive advantage can be explained by managerial competence and the role of chance and luck (Barney 1986; Arthur 1989; Denrell 2004).

Within this tradition, superior performance is explained by incumbency advantages which accumulate through random mechanisms stimulated by path dependency (DiPrete and Eirich 2006; Arthur 1989).

More recently, there has been an attempt to bridge both views by acknowledging that both differences in capabilities and random events have an impact on performance over time (Denrell et al. 2013). Denrell et al. (2013) proposed the Bayesian approach as the most suitable method for inferring capabilities from observed data. Most importantly, by accounting for underlying stochastic processes, Bayesian models can separately investigate elements of sustained competitive advantage and compute conditional probabilities of the role of firm-dependent components versus components dependent on accumulated prior performance.

One of the key methodological strengths of Bayesian analysis is that it recognises the confounding effect of stochastic factors affecting performance. However, it was not possible to adopt such approach in the present research because Bayesian models tend to measure superior performance over multiple periods of time in order to estimate its sustainable nature (Hansen et al. 2004; Hahn and Doh 2006; Denrell et al. 2013; Powell 2001), for which the current project had no such data.

The use of advanced econometric methods in investigating the role of heterogeneity in capabilities is not limited to the Bayesian approach. Another group of RBV scholars employed ideas of production economics to study the role of capabilities in explaining differences in firms' performance (Dutta et al. 1999; Dutta et al. 2005). Production economics literature proposed to measure firms' performance as a ratio of productivity comparing the level of input resources that are necessary to yield a certain level of outputs (Coelli et al. 2005; Fried et al. 2008). A firm that can attain a maximum output level with a set of certain inputs creates a technological best-practice benchmark in the industry, a so-called production frontier, and firms that operate below this frontier are defined as technically inefficient (Coelli et al. 2005). As such, measurement of efficiency implies a comparison of actual performance with maximal performance located on the production frontier (Fried et al. 2008) and is an *"empirical estimation of the extent to which the observed agents achieve the theoretical ideal"* (Greene 2008 p.93).

Using the core input-output concept of the economic theory of production, Dutta et al. (1999) suggested that capabilities can be operationalised and measured as a function of production efficiency. Following seminal work by the authors (Dutta et al. 1999), there has been a stream of research that took the same path (Narasimhan et al. 2006; Xiong and Bharadwaj 2011; Bahadir et al. 2008; Feng et al. 2015; Mahmood et al. 2011). Under the input-output perspective, capabilities refer to the efficient deployment of a set of available resources to attain specific organisational goals (Dutta et al. 2005). Estimation of capabilities using the input-output framework offers two significant advantages. Operationally, it enables to infer capabilities as a function of transformational efficiency, while methodologically, it allows using secondary and archival data to perform the calculation procedure (Dutta et al. 1999).

The estimation of technical and efficiency change can be carried out empirically using one of the two known benchmarking approaches, namely Data Envelopment Analysis (DEA) mathematical technique and Stochastic Frontier Analysis (SFA) econometric technique. There is a constant academic dispute about the validity and suitability of the non-parametric DEA versus the parametric SFA technique (Fried et al. 2008). Although the DEA is a less data-sensitive approach because its linear specification can handle zero-valued inputs and outputs, or multiple outputs in a single equation, it is merely a mathematical calculation which does not account for the random error of the studied phenomenon (Fried et al. 2008). To overcome this significant limitation of the non-parametric productivity analysis, Simar and Wilson (1998) developed a procedure for constructing the confidence intervals using the bootstrap method to correct for the bias of the DEA estimators which arises due to the inability of the data envelopment method to incorporate statistical noise. However, despite such methodological advancement, implementation of bootstrap methods for inference in frontier methods remains challenging, and misspecification of restrictions in the estimation model will generate inconsistent results if the data already contain noise (Simar and Wilson 2008).

The frontier approach, on the other hand, is an econometric method which offers a way to estimate the stochastic component of the transformation efficiency, but requires the data to fit a number of underlying statistical assumptions, which creates room for specification error (Fried et al. 2008). The Cobb-Douglas and translog models prevail the econometric inefficiency estimation literature, although their logarithmic specification cannot accommodate zero-valued inputs and outputs. The primary assumption is that no output can be produced unless all inputs are above zero (non-negativity, weak essentiality and monotonicity assumptions[23]), and the firm becomes infinitely inefficient as soon as a single input or output becomes zero (Greene 2012 p.174). However, in reality, this assumption may not necessarily hold—a firm may still be able to achieve a certain level of production output even when one of its inputs is absent. Because of its ability to calculate the random noise similar to the Bayesian approach, the SFA was deemed a more sophisticated method for the current estimation procedure than the DEA. It is also a preferred tool in the marketing field, which further supports the decision in favour of the use of the econometric rather than a mathematical approach for estimating efficiency. The inability of the stochastic frontier estimation procedure to accommodate zero values was dealt with via data transformation, whereby a small constant was

[23] According to Chambers (1988) production functions must meet the following four underlying assumptions: (i) non-negativity – the value of input x is a positive number; (ii) weak essentiality – production of output requires at least one input x; (iii) monotonicity – inputs x are non-decreasing; (iv) concavity – inputs x are non-increasing.

added to all values to be able to apply a logarithmic specification. Such technique is widely used in statistics and econometrics and is considered a valid approach in dealing with the problem of zero values when a logarithmic function is to be used (Cohen et al. 2003). Data transformations are discussed in more detail in the next chapter. Additionally, data were inspected for the presence of any significant outliers which could bias the estimates, which is of vital importance in any frontier modelling method (Simar and Wilson 2008).

Stochastic Frontier Production function developed independently by Aigner et al. (1977), and Meeusen and Broeck (1977) is an extension of a classical regression model and is based on the theoretical notion that a production function *"represents an ideal, the maximum output attainable given a set of inputs"* (Greene 2008). The function can be written as the following model with a simple exponential specification (Battese and Coelli 1992; Battese and Coelli 1995):

$$y_{it} = f(x_{it};\ \beta)\exp(v_{it-}\ u_{it})$$

where

y_{it}	=	output of firm i in time t
$f(x_{it};\ \beta)$	=	function of a vector
x_{it}	=	factor inputs
β	=	vector of unknown parameters
v_{it}	=	random error that accounts for statistical noise and can be positive or negative
u_{it}	=	non-negative random variable of the $N(\mu, \sigma^2)$ distribution associated with technical inefficiency in which μ is an unknown scalar parameter

Thus, the random components v_i and u_i determine the stochastic nature of the frontier models and μ and σ^2 parameters define firm-varying effects (Battese and Coelli 1992).

Typically, stochastic frontier analysis is conducted by using the Cobb-Douglas logarithmic function, so the above model can be rewritten as follows (Coelli et al. 2005):

$$log(y_{it}) = \underbrace{\beta_0 + \beta_1 \times log(x_1) + \beta_2 \times log(x_2) + \dots \beta_n \times log(x_n)}_{\text{deterministic frontier}} \times \underbrace{\exp(v_{it})}_{\text{noise}} \times \underbrace{\exp(-u_{it})}_{\text{inefficiency}}$$

The estimation procedure of the above function required that the random terms v_i and u_i meet assumptions similar to those of the conventional linear regression model: the terms must be distributed independently of each other and be uncorrelated with x_i factor inputs, while the inefficiency component u_i must meet an additional criterion of strict non-zero mean (Coelli et al. 2005).

Much of the stochastic frontier analysis is aimed at estimating the inefficiency component. The most widely used output-oriented measure of technical efficiency is calculated as the ratio of the firm's output relative to the potential output of a fully-efficient firm given the same set of input factors, which determines the production frontier (Coelli et al. 2005). Hence, the function of technical efficiency (TE) can be expressed in the following way (Coelli et al. 2005):

$$TE_i = \frac{\exp(x_i\beta + v_i - u_i)}{\exp(x_i\beta + v_i)} = \exp(-u_i)$$

The SFA procedure was carried out in the 'Frontier' package of the R-studio statistical programme. First, maximum likelihood estimates were produced under the Error Components Frontier specification (Battese and Coelli 1992). These estimated parameters are starting values to determine the stochastic production frontier (Coelli et al. 2005). Next, technical efficiencies were predicted in relation to the maximum achievable output, indicating that inefficiency decreases the output variable. One of the most important parameters of the log-likelihood estimation is gamma, which can be expressed as $\gamma = \sigma_u^2/\sigma^2$, and high values of gamma indicate that the inefficiency component accounts for a large proportion of the variation in the error term (Coelli et al. 2005). The measure of technical efficiency takes the value between zero and one, and can also be expressed as a percentage, with 100% attained by the best-performing firm. The summary of stochastic frontier estimation results is reported in Appendix 4.

The definition of capability employed in the present research refers to the ability to transform resources through the efficient productive activity to achieve higher-order goals (Dutta et al. 2005). Three types of capabilities, namely managerial, intellectual and R&D capabilities were utilised in the conceptual framework, and their transformational functions are described in detail below.

Managerial Capability

Prior literature outlined three pillars of dynamic managerial capabilities, which can also be referred to as managerial operational capabilities (Helfat and Martin 2015)—managerial cognition, social capital, and human capital (Adner and Helfat 2003). These categories of managerial resources have distinct as well as interaction effects on managerial capabilities (Adner and Helfat 2003) and draw on previous experience (Helfat and Martin 2015). These three underpinning components form the basis for empirical measurement of managerial capabilities.

Some of the empirical approaches employed in previous research were criticised for an overarching tautological assumption that managerial capabilities directly measure firm performance (Helfat and Martin 2015). To overcome this limitation, more recent studies proposed to follow a chain-of-effects empirical approach, whereby the impact of managerial capabilities is expressed as strategic change, which presents an intermediary outcome leading to firm performance (Martin 2011).

Managerial capabilities display path dependency (Teece et al. 1997) and develop through learning (Zollo and Winter 2002). A recent review of managerial dynamic capabilities literature by Helfat and Martin (2015) provided a summary of variables used to measure three components of the construct; namely, managerial cognition, social capital, and human capital which can be utilised separately or in combination, as well as measures of strategic change (summary of measures is presented in Appendix 5). According to this review, there is a significant body of research that found evidence of the impact of human capital characteristics such as education and experience on strategic change efforts and outcomes (Helfat and Martin 2015).

Following the logic behind previous empirical studies, the present research operationalised managerial capability as a function of human capital resources that relate to strategic change. Strategic change was expressed in terms of international diversification, while human capital in terms of prior experience. International diversification is viewed as a complex strategic decision because of opportunities and threats associated with geographic expansion (Tihanyi et al. 2000). Management capability functions as a link between human capital and performance in dynamic environments (Hsu and Wang 2012).

The conceptualisation adopted by the current study implies the following managerial capability transformation function:

$$Innovation\ Proliferation = f(Commercial\ Experience, Inventive\ Capacity)$$

where

Innovation proliferation	=	total number countries where the firm was granted patents in <t
Commercial experience	=	total number of years of manager's experience in commercial positions in any sector in <t
Inventive capacity	=	total number of patent applications by the manager in year <t

Prior research has measured geographic diversification, or firm's dispersion of activities, using patent statistics (Bergek and Bruzelius 2010). Grupp and Schmoch (1999 p.385) highlighted that *"patent protection establishes market access barriers and, as a result, creates a temporary monopoly on product availability or facilitates a head start in application of technology"*. The fact that patents are granted by national patent offices means that inventions are protected within boundaries of one country. Considering the time and financial resources necessary to file a patent, firms need to make intentional decisions on the territorial coverage of intellectual property rights and future markets of technology protection (Grupp and Schmoch 1999). Therefore, if the firm files a patent in the country where it is headquartered, it indicates the pursuit of a domestic market strategy. On the other hand, filed patents in a number of countries demonstrate a firm's intention to manufacture, market or license the invention in these countries (Grupp and Schmoch 1999).

Since all firms in the sample are classified as domestic, internationalisation of protective activities is not only necessary to protect against imitation in the global arena but is also a strategic move. Management literature has paid particular attention to strategic patenting and viewed intellectual property protection as a link with competitiveness and an outcome of effective management (Granstrand 1999). In the same vein, scholars have recognised that benefits of innovation can be realised through intelligent management of patenting activities (Teece 1986). Drawing on these arguments from prior research, present study expressed the output of managerial capability as innovation proliferation, which represents the motive to diversify internationally and is linked to the concept of strategic change.

Two input variables were determined as suitable measures of human capital characteristics. Evidence exists that managers' commercial experience positively affects firm's new product development capabilities (Deeds et al. 1999). Therefore, commercial experience is an important indicator of the quality of manager's human capital. The measure of commercial working experience was adopted from prior literature (Minola and Giorgino 2008) as the number of years spent in managing positions, although it has also been measured as a dummy variable of whether or not the member of the TMT had prior management experience (Deeds et al. 1999). Operationalisation of the measure of inventive capacity, which is the second input variable, was described in the section above.

The above function can be rewritten as the Cobb-Douglas specification:

$$log(Innovation\ Proliferation) = \beta_0 + \beta_1 \times log(Commercial\ Experience) + \beta_2 \times log(Inventive\ Capacity) \times exp(V_{it}) \times exp(-U_{it})$$

Principal Investigator's Intellectual Capability

Given that the sample is made up of small private firms, the role of each individual member involved in project development is critical. In particular, the purpose of principal investigators is to guide R&D efforts and achieve innovation outcomes. Therefore, present research measures intellectual capability at the individual level and uses principal investigator as the unit of analysis. Rooted in human capital literature, intellectual competence has been traditionally assessed in terms of knowledge, expertise and skills (Subramaniam and Youndt 2005). A study by Hsu and Wang (2012) has operationalised employee productivity as work ability and uniqueness of employees' knowledge as employee value added. In line with such reasoning, principal investigator's output is expressed as an academic impact, which is an outcome of a combination of distinct specialised knowledge stocks.

In line with the definition of intellectual capability expressed as the intelligent deployment of cognitive capacities (Alvesson and Spicer 2012), the transformation function can be formulated as follows:

$$Academic\ Impact$$
$$= f(Quality\text{-}Adjusted\ Academic\ Competence, Knowledge\ Appropriation, Inventive\ Capacity)$$

where

Academic impact	=	h-index of the principal investigator defined by Scopus in year t
Quality-adjusted academic competence	=	citation-weighted publications of the principal investigator in year <t
Knowledge appropriation	=	ratio of self-citations by total documents published by the principal investigator in year <t
Inventive capacity	=	total number of patent applications by the principal investigator in year <t

H-index was retrieved from the Scopus database and is designed to measure both the productivity and impact aspects of the published scholarly work (Elsevier 2015). The measure was developed by Hirsch and is defined as *"the number of papers with citation number higher or equal to h"* (Hirsch 2005 p.1). In other words, an h-index of 10 would suggest that out of all publications, ten documents were cited ten times or more.

The literature on productive efficiency acknowledges that input and output variables may differ from one firm to another in terms of quality and recommends adjusting variables to account for quality differences by directly incorporating quality characteristics in the model or by attaching numerical weights to relevant variables (Coelli et al. 2005). To account for differences in the value of patented knowledge, scholars have developed measures that adjust patents by their quality (Trajtenberg 1990; Dutta and Weiss 1997; Levitas and McFadyen 2009). The measure of citation-weighted publications was adopted from Dutta et al. (1999) and was computed in three steps. First, the average number of citations received by all documents published by all principal investigators in the sample was calculated. Then, the weight was determined as a ratio of the number of principal investigator's citations to the sample average. This weight was then assigned as a multiplier to the total number of documents published by the principal investigator to arrive at the value of citation-weighted publications.

The second input variable refers to knowledge appropriation. The topic of how firms appropriate value from their inventions has received significant attention in strategic management field (Teece 1986). Effectiveness in translating ideas that constitute earlier inventions into the flow of future inventions has been coined generative appropriability and has been measured as the proportion of firm's inventions, patents, products or citations that are generated from firm's prior inventions or patents (Ahuja et al. 2013). In the same vein, because knowledge accumulation is embodied in patents and citations signify new knowledge that streams from these patents, the propensity of firms to cite their own patents indicates the creation of internal and firm-specific innovative knowledge stock (Wang et al. 2009). This logic was adopted to construct a measure of individual-specific knowledge assets. Knowledge appropriation was defined as the degree to which the individual is building upon its previous know-how. The variable was measured as the proportion of principal investigator's self-citations that was exploited in total publications of the principal investigator.

Operationalisation of the measure of inventive capacity, which is the third input variable, was described in the section above.

The frontier function can be expressed as the Cobb-Douglas specification:

$$log(Academic\ Impact) = \beta_0 + \beta_1 \times log(Quality\text{-}Adjusted\ Academic\ Competence) + \beta_2 \times log(Knowledge\ Appropriation) + \beta_3 \times log(Inventive\ Capacity) \times exp(V_{it}) \times exp(-U_{it})$$

R&D Capability

The purpose of R&D efforts is to generate technological innovations (Dutta et al. 1999). Innovative activities frequently call for complementary resources, such as capabilities (Teece 1986). Previous research suggested that path dependency is an important innovation mechanism, and firm's prior knowledge stock is an essential prerequisite of inventive capability (Cohen and Levinthal 1990). Thus, a firm's technological and knowledge stocks are necessary elements of R&D capability. As was noted previously, firm's absorptive capacity depends on (although is not limited to) absorptive capacities of its individual members (Cohen and Levinthal 1990). Therefore, in addition to firm's accumulated knowledge, intellectual capability of a key scientist, i.e. principal investigator, is a key component of a firm's innovative output.

Following the logic of the operationalisation proposed by Dutta et al. (1999, 2005), the measure of R&D capability can be expressed by the frontier function below:

$$Invention\ Activity = f(Quality\text{-}Adjusted\ Patenting\ Output, Knowledge\ Breadth, PI's\ Intellectual\ Capability)$$

where

Invention activity	=	total number of patent applications by firm in year t
Quality-adjusted global patenting output	=	citation-weighted patent stock by firm in year <t
Knowledge breadth	=	total number of patent classes firm has acquired in year <t
PI's intellectual capability	=	efficiency scores derived from stochastic frontier analysis (specification of the measure outlined above)

Patentable knowledge is a manifestation of inventive activity and serves three primary strategic purposes: protection of intellectual property, commercialisation of new know-how in the form of product innovation or licensing, and an indication of R&D performance (Blind et al. 2006). Here, inventive activity was operationalised as firm's patenting performance, measured by the count of filed patent applications (Andries and Faems 2013).

Citation-weighted patent stock was calculated in the same way as principal investigator's citation-weighted publications described in the previous paragraph, whereby weight was incorporated into the measure of patent stock to account for differences in quality.

Previous research operationalised the breadth of the firm's knowledge as the number of research domains the firm was active in (Al-Laham and Souitaris 2008) and an average number of patent technological subclasses of firm's patents (Prabhu et al. 2005; Patel and Jayaram 2014; Vural et al. 2013). Global patenting offices use an international patent classifications (IPC) system to allocate patents to appropriate technological classes. The count of patent classifications has been used as a proxy to measure the breadth of knowledge contained in a patent, which indicates its quality and future potential value (Lerner 1995). Building on this argument, knowledge breadth was measured as the stock of firm's IPCs.

The above frontier function can be formulated as the Cobb-Douglas econometric specification:

$$log(Invention\ Activity_t) = \beta_0 + \beta_1 \times log(Quality\text{-}Adjusted\ Patenting\ Output) + \beta_2 \times log(Knowledge\ Breadth) + \beta_3 \times log(PI's\ Intellectual\ Capability) \times\ exp(V_{it}) \times exp(-U_{it})$$

Controls

Non-woman-owned

One of the goals of the SBIR and STTR programmes is to encourage participation in innovation and entrepreneurship by socially and economically disadvantaged small businesses and women-owned small businesses (SBIR 2015). To qualify as a woman-owned small business, a firm must be at least 51% owned and controlled by one or more women, and primarily managed by one or more women who holds U.S. citizenship. To control for potential effects of such participants, woman-owned businesses were reverse-coded as a dummy variable of whether the firm is woman-owned (0) or not (1).

Non-minority-owned

Some ethnic minority groups are presumed to be socially and economically disadvantaged. To qualify as a minority-owned small business, the firm must be 51% or more owned and controlled by at least one member of one of the following groups: African Americans, Hispanic Americans, Native Americans, Asian-Pacific Americans, Subcontinent Asian Americans, Alaska Native Corporations, Indian Tribes, Native Hawaiian Organizations and Community Development Corporations. Minority-owned businesses were reverse-coded as a dummy variable of whether the firm is minority-owned (0) or not (1).

Non-HubZone-owned

The Historically Underutilized Business Zones (HubZone) programme helps small businesses in urban and rural communities gain preferential access to federal procurement opportunities. To qualify as a HubZone-owned small business, the firms' principal office must be located in an area designated as a HubZone and in part employ staff who live in a HubZone. HubZone-owned businesses were reverse-coded as a dummy variable of whether the firm is located in a HubZone (0) or not (1).

Industry Volatility

Dixit and Pindyck (1994) introduced two concepts of uncertainty relevant to the real options reasoning–technical and input uncertainty. While technical uncertainty is project-specific and can be resolved through investments, input uncertainty is external to the firms and is particularly manifested in the ROR logic by the relevance of the defer option, which allows waiting until more information becomes available to resolve exogenous uncertainty. To account for the type of uncertainty, which is relevant in real options models and cannot be reduced through project-specific investments, a macro measure of industry-specific uncertainty was used as a control mechanism.

Industry stock return volatility was used as a proxy for industry risk (Peters and Wagner 2014). More volatile stock prices signal heterogeneity in technology and productivity levels of market participants, which cause demand shocks, potential changes in the industry environment and uncertainty in future business conditions (Peters and Wagner 2014). In real options theory, uncertainty is an important element in assessing the value of the financial or technology option as real options are perceived to be affected by the same factors as the stock price volatility (McGrath 1997). As such, by analogy with financial theory but counter to conventional logic, under the real options reasoning high uncertainty has a *positive* impact on investment opportunities that result from the flexibility to continue or discontinue the project (Trigeorgis 2005). With potential losses limited to the initial price of the option, the larger the variance of expected revenues and costs caused by uncertainty in the market, the greater the value of the option and total potential gains, making options investments more attractive (McGrath 1997). In other words, high market volatility increases the potential gain from holding an option, while low market volatility increases the potential gain from exercising an option (Bowman and Hurry 1993).

The variable construction procedure was adapted from the paper by Peters and Wagner (2014). First, industry classifications were recorded for each company in the sample from the Hoover's database or firms' LinkedIn profiles. Then, these industry classifications were matched with the Standard Industrial Classification (SIC) code list reported in the EDGAR database of the U.S. Securities and Exchange Commission (SEC). Next, four-digit SIC codes were grouped according to the Fama-French classifications (Fama and French 1997) of 49 industries (Table 5-7). Finally, a list of market returns on a portfolio of 49 industries was retrieved from the Kenneth R. French Data Library (2015). To construct an industry-level measure of risk proxy, industry stock return volatility was computed using 5-year windows of the average equal-weighted annual returns of the Fama-French 49 industries. The variable was operationalised as the absolute deviation of the average annual equal-weighted returns in year t-1 from the average annual equal-weighted returns in the 5-year rolling window:

$$D_i = |Average\ Annual\ Equal\text{-}Weighted\ Returns_{\ t-1} \\ - Average\ Annual\ Equal\text{-}Weighted\ Returns_{\ t-1,t-2\ldots t-5}|$$

To address timing issues and reduce potential simultaneity concerns (Peters and Wagner 2014), volatility instruments were lagged by one fiscal year of the award announcement date or reported sales date.

Table 5-7: Matching procedure of SIC industries in the sample with Ken French's industry classifications

Ken French's SIC Industry Definition	Number of cases in the category	SIC Industry	SIC Code	Number of cases in the industry
Business Services	203	Advertising Agencies	7311	1
		Computer Processing and Data Preparation and Processing Services	7374	5
		Computer Related Services	7379	4
		Business Services	7389	5
		Engineering Services	8711	7
		Surveying Services	8713	1
		Commercial Physical and Biological Research	8731	122
		Commercial Economic, Sociological, and Educational Research	8732	5
		Noncommercial Research Organizations	8733	35
		Testing Laboratories	8734	7
		Management Services	8741	1
		Management Consulting Services	8742	2
		Business Consulting Services	8748	6
		Services	8999	2
Chemicals	1	Industrial Inorganic Chemicals	2819	1
Computer Software	18	Computer Programming Services	7371	9
		Prepackaged Software	7372	2
		Computer Integrated Systems Design	7373	6
		Information Retrieval Services	7375	1
Construction	7	Heavy Construction	1629	3
		Special Trade Contractors	1799	4
Construction Materials	1	Reconstituted Wood Products	2493	1
Electronic Equipment	4	Communications Equipment	3669	1
		Electron Tubes	3671	1
		Semiconductors and related devices	3674	2
Healthcare	16	Offices and Clinics of Doctors of Medicine	8011	2
		Medical Laboratories	8071	10
		Home Health Care Services	8082	2
		Health and Allied Services	8099	2
Measuring and Control Equipment	11	Instruments for Measuring and Testing of Electricity and Electrical Signals	3825	1
		Laboratory Analytical Instruments	3826	2
		Optical Instruments and Lenses	3827	3
		Measuring and Controlling Devices	3829	5
Medical Equipment	21	Surgical and Medical Instruments and Apparatus	3841	9
		X-Ray Apparatus and Tubes and Related Irradiation Apparatus	3844	5
		Electromedical and Electrotherapeutic Apparatus	3845	7
Pharmaceutical Products	68	Medicinal Chemicals and Botanical Products	2833	3
		Pharmaceutical Preparations	2834	27
		In Vitro and In Vivo Diagnostic Substances	2835	15
		Biological Products, Except Diagnostic Substances	2836	23

Retail		Optical Goods Stores	5995	1
		Miscellaneous Retail Stores	5999	2
Wholesale	15	Computers And Computer Peripherals Equipment And Software	5045	1
		Medical, Dental, and Hospital Equipment and Supplies	5047	10
		Professional Equipment and Supplies	5049	1
		Drugs, Drug Proprietaries, and Druggists' Sundries	5122	3
N/A	15	N/A	N/A	15
Total	**383**			

State Innovativeness

The theory of entrepreneurship posits that geographic location facilitates firm's access to the skilled technical personnel and the streams of knowledge (Deeds et al. 1999). Therefore, geographic-specific resources have an impact on firm's innovation capacity. To control for location effects, the measure of U.S. states' innovativeness was constructed to get a proxy for geographic attractiveness. The ranking list of the most innovative U.S. states was retrieved from Bloomberg's Visual Data platform (2015). Bloomberg is widely used in financial and economics research as a reliable source of data and insights. For current purposes, the ranking table by Bloomberg was preferred over other sources due to the comprehensiveness of the methodology which evaluated the U.S. states and the District of Columbia on six innovation factors[24] to arrive at the averaged final score expressed on the scale from 0 to 100 comprising the states' innovation index. The data on six innovation factors stated in the report were collected from Bloomberg, Bureau of Economic Analysis, Bureau of Labour Statistics, National Science Foundation, U.S. Census, U.S. Patent and Trademark Office. Scores from the Bloomberg ranking table were applied to firms in the database by the state they are registered in, with higher scores indicating more innovative U.S. states. The downside of using Bloomberg Innovation Index was that historical data were not available, so only the scores from the most recently updated 2013 report could be used for the analysis.

[24] 1. Number of professionals in STEM as a percentage of the state's population; 2. STEM degree holders as a percentage of the state's population; 3. Patents for inventions granted by the state of origin as a percentage of the U.S. total; 4. State government R&D expenditure as a percentage of the U.S. total; 5. Productivity: (i) Gross state product per employed person; and (ii) three-year change in productivity; 6. Public technology companies in industries such as aerospace and defense, biotechnology, pharmaceuticals, renewable energy, technology as a percentage of all public firms domiciled in the state.

Firm Age

Another factor that influences uncertainty surrounding small firms is their age (Sanders and Boivie 2004; Daily et al. 2005). Organisational ecologists demonstrated evidence that age can have a negative effect on survival rates of new and adolescent firms (Hannan and Freeman 1984; Brüderl and Schüssler 1990). Firm age affects the availability of historical information related to firms' operational, financial and strategic performance. Since younger firms have little objective performance data to reveal to investors, their performance prospects are harder to estimate (Megginson and Weiss 1991; Mikkelson et al. 1997). Consequently, younger firms are associated with higher risk and uncertainty, which has an impact on investment patterns (Sanders and Boivie 2004).

In previous literature, firm age has been operationalised as the number of years from firm inception to a particular point in time or event of interest (Urbig et al. 2013; DeCarolis et al. 2009). Similarly, firm age was measured as the number of years that elapsed since the date the firm was founded until the project award date. Firm's age was retrieved from companies' websites, and, when not available, from firms' LinkedIn profiles or Bloomberg Business Week.

Project Cohort

In line with previous research, the control for timing of application was included (Kirsch et al. 2009). Project cohort refers to the year in which the project was funded. Award years were coded as follows: 2006 as 1, 2007 as 2, 2008 as 3, 2009 as 4, 2010 as 5, 2011 as 6 and 2012 as 7.

5.6 Analytical Approach

By its nature, statistical analysis is relevant to research projects that follow a positivistic strategy, and it is built on the fundamental notion of probability distributions of various outcomes (Remenyi et al. 1998). However, if collected data were simply run through a statistical package, it is unlikely that it would produce useful insights. Instead, gathered evidence first needs to be looked at to understand whether the expected patterns persist in the data. This stage entails univariate analysis and can be conducted using exploratory and descriptive statistics (Bryman and Bell 2011). Then, to ensure that the observed patterns occur not simply by chance, but reveal some underlying processes, more detailed statistical analysis should be performed (Remenyi et al. 1998). Hypothesis testing procedure calls for the mathematical logic of more robust statistical tools. As the first step, bivariate relationships between variables can be scrutinised using correlation analysis and contingency tables. Finally, multivariate analysis can be performed to examine the simultaneous effects and interactions of a number of variables on the dependent variable (Bryman and Bell 2011).

Data Analysis Tools

Multi-level data can be analysed using hierarchical linear modelling, structural equation modelling or multi-level analysis. Before any of these techniques can be used, data need to be evaluated for basic multi-level assumptions such as within and between group correlations using ANOVA (Dansereau and Yammarino 2006). In other words, to make valid statistical inferences from the multi-level analysis, there should exist between-level correlation of constructs (Heracleous and Jacobs 2008).

Despite using multi-level data, multi-level modelling was beyond the scope of the current project because the sample size of the lower level project and individual variables was the main restricting factor from the applicability of multi-level modelling. While it is generally acceptable for multi-level models to have unbalanced sample sizes at each level, they should be of appropriate sizes (Snijders 2005). In the current case, however, the sample has been balanced in a way that for each firm there were only names of two individuals available, and between one and seven projects. Hence, it would not have been possible to determine the between-firm variances of effects between project-level and individual-level variables. To estimate the multi-level model, instead of drawing a random sample of projects, the entire portfolio of firm's projects should have been used. Even then, multi-level modelling would have been limited in its ability to provide reliable estimations, because many firms that participated in the SBIR initiative only had one Phase I award.

Because the aim of the project is to investigate the outcomes of government venture funding, the ROR model has multiple measures of performance. Hence, the data analysis method had to be chosen based on its ability to calculate regression estimates for different equations with multiple dependent variables.

One such modelling approach is the systems method, which instead of estimating parameters of each equation separately, estimates all theoretically relevant structural equations as a set (Kennedy 2003). Simultaneous equations procedures have been the main point of difference between econometrics and traditional statistics (Kennedy 2003). However, the simultaneous equations models have been criticised for often producing inconsistent forecasts and unreasonably narrow confidence intervals (Kennedy 2003). Additionally, it was recognised that equations may be connected not through their direct simultaneous interaction, but because of the interaction of their error terms (Kennedy 2003). To address such cases, Zellner (1962) proposed a technique called seemingly unrelated regression (SUR) which offers a number of benefits. First, theoretically related sets of equations can be modelled jointly. Second, the method produces more consistent and efficient estimates because it allows for contemporaneous correlation of error terms across multiple equations. To compare, while OLS equation by equation can also be used for hypothesis testing, it only allows to estimate coefficients within an equation but does not take into account cross-equation restrictions (Wooldridge 2010).

SUR can be expressed as a set of individual equations written in one macro equation:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_n \end{bmatrix} = \begin{bmatrix} x_1 & & \\ & x_2 & \\ & & x_n \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_n \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_n \end{bmatrix}$$

or

$$Y_i = x_i \beta_i + e_i$$

where there are N equations, subscript i refers to the ith equation.

The equation explains the principle underlying the name of the seemingly unrelated regression method: because each equation has its own vector β_i, it seems that equations are not related; however, correlated error terms provide links between different equations which improves efficiency of estimation (Wooldridge 2010).

Because of these major advantages, the econometrics field has been in favour of the use of seemingly unrelated regression estimation method (Wooldridge 2010). Seemingly unrelated regression has also gained popularity in marketing literature (e.g. Vorhies et al. 2009) because it allows capturing the simultaneous and sequential nature of underlying strategic processes.

Nevertheless, for this method to be more efficient over OLS equation by equation, it has to meet one of the two underlying conditions: either (i) x_i are all different, or (ii) the variance-covariance matrix of e_i is not diagonal (Kennedy 2003). The Breusch-Pagan (1980) Lagrange multiplier statistic provides means to test the second assumption by estimating whether the errors depict interdependency. If error terms of different equations are not correlated and if there are no endogeneity issues among variables, the equation by equation methods should be used instead to produce consistent and unbiased estimates (Kennedy 2003).

Even though structural equation modelling (SEM) technique can also be used to model a series of simultaneous equations, one of its significant limitations is that it cannot handle multiple categorical variables (Bollen 1989). Given that the conceptual model proposed in the current study required incorporation of nominal data, seemingly unrelated regression method was deemed the most appropriate method to perform regression procedure for the systems of equations.

Seemingly unrelated regression estimation procedure was carried out in STATA statistical package using the 'sureg' command, which is built on the feasible generalised least-squares (FGLS) algorithm outlined by Greene (2012). To test hypotheses of the signalling framework, however, equations did not need to be estimated simultaneously. Therefore, when the dependent variable was continuous, the OLS method was used, while for binary dependent variable Logit models were employed.

Regression equations were modelled using standardised data to minimise heterogeneity across different units of measurement that varied across the constructs in the model (Vorhies et al. 2009). Data standardisation procedure was carried out in STATA under the 'egen' command, which created metric variables with the mean value of 0 and standard deviation value of 1.

5.7 Concluding Remarks

An overview of potential methodologies concluded that it is not possible to evaluate research approaches in any absolute terms, and each strategy has something to offer (Gill and Johnson 1997). Therefore, the research methodology was designed in a way that reflects the philosophical understanding of the research problem and helps answer the research questions in the most efficient manner. The positivistic research philosophy adopted by this study follows that of a natural scientist, whereby quantitative data were collected to establish cause and effect relationships between a number of variables that constitute the studied phenomena, hypotheses were generated to test theory and facts were gathered to provide the basis for variable operationalisations. Archival design was chosen to compile a multi-level longitudinal dataset from publicly available multi-source domains, which was analysed using econometric and statistical exploratory and regression techniques.

Chapter 6 - Data Preparation & Descriptive Analysis

6.1 Introduction

Methodological foundations discussed in detail in the previous chapter laid the basis for the formative data analysis. Having generated a workable dataset with operational variables, attention is now drawn to the issues concerning the data that will be used subsequently for model building.

The objective of this chapter is threefold. First, it outlines the steps taken to convert raw data into a working format. The steps include missing value analysis, imputation procedure and outlier analysis. Second, all the key assumptions underlying multivariate modelling techniques are tested and involve examination of normality, linearity, homoscedasticity, multicollinearity and endogeneity. Finally, data undergoes preliminary exploratory analysis by examining descriptive and correlation statistics to get a feel for patterns in the sample and between individual variables.

6.2 Data Preparation

After all variables were coded in line with operationalisations, raw data needed to be checked for credibility, consistency and completeness (Chatfield 1995) prior to applying measurement formulas and any statistical procedures. First, Excel spreadsheets containing data on different levels of measures were compiled into one macro dataset and then cleaned or formatted. Next, to check for any recording, typing, transcription, inversion or repetition errors (Chatfield 1995) data were examined visually and by computing the mean, minimum and maximum values to identify any cases that fall outside the logical range. Finally, all values that were detected as suspect were checked against the original data and corrections were made when necessary.

Missing Value Analysis

Missing value analysis concerns the analysis of unobserved entries in the data matrix which consists of rows of observations, or cases, and columns of variables (Little and Rubin 2002). The initial sample database consisted of 383 cases and 48 variables, 15 of which were dummy variables, including one dependent dichotomous variable. Missing value analysis was conducted in the SPSS package to diagnose the extent, patterns and mechanisms of missing data in the initial sample.

Step 1: Determine the Extent of Missing Data

As suggested by Hair et al. (2010), cases or variables with 50% or more missing data should be deleted, while cases or variables containing between 15% and 50% of missing data require judgment on a case by case basis. As a first step, the amount of missing data were tabulated to establish the degree of missing data by case.

Appendix 6 displays that 7 cases had 40% or more missing data. These cases were identified for deletion due to an excessive number of missing values which ranged from 40.5% to 51.3%, leaving a sample of 376 observations. Next, after deletion of cases with the extremely great extent of missing values, data were analysed by variable.

As can be seen from Appendix 7 the extent of missing values ranged from 0% to 35.1%. Missing values were concentrated in a specific set of questions, mostly concerning individual-level characteristics, suggesting potential presence of a non-random pattern which merits further investigation.

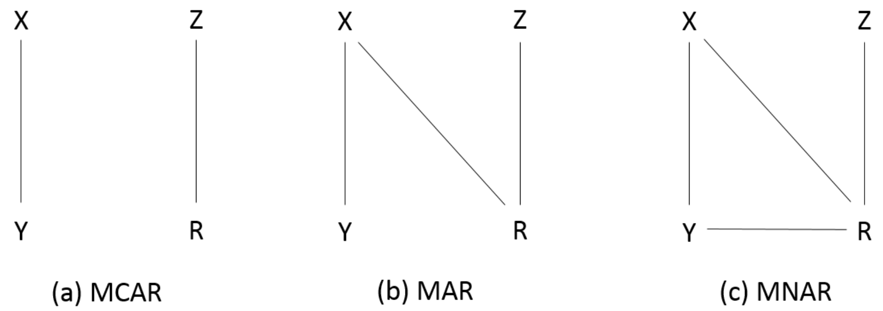
Step 2: Diagnose the Randomness of the Missing Data

Missing data is a widespread problem in all fields of the social sciences. The majority of statistical packages employ a complete-case analysis as a default approach and exclude observations and variables that have missing values from the analysis. Such approach was described as 'inappropriate' because it does not allow to make statistical inferences from the entire population (Little and Rubin 2002). Therefore, to identify techniques that are more suitable than complete-case analysis in the presence of unobservable values, the patterns and mechanisms of missing data need to be specifically investigated for the presence of random distribution across the variables and cases (Little and Rubin 2002). The pattern of missing data refers to missing and observed values in the data matrix, while the mechanism of missing data denotes the relationship between the missingness pattern and the values of variables in the data matrix (Little and Rubin 2002).

First, to determine the pattern of missingness, the data were visually inspected using Multiple Imputation function in SPSS. The patterns chart in Appendix 8 depicts that missing values were concentrated in the lower right corner of the chart with some patches of non-missing values, and with non-missing data in the upper left portion. Thus, the data exhibited both monotone and general data missingness patterns, as demonstrated in Appendix 9. Monotone patterns usually arise in repeated-measures or longitudinal research designs as a result of a respondent dropping out of the study, which causes attrition (Schafer 1997). Given that the latter is not the case in the present project as missing values can only be attributed to data unavailability in public sources, the monotone pattern was merely a result of reordering the variables according to their missingness rates by the statistical package (Schafer 1997). Therefore, as in survey research design, the instance presented here is that of item nonresponse, which refers to missing values on a set of particular variables, and because of the random distribution of missing values, it is typically called a general missing data pattern (Little and Rubin 2002). Such pattern is best handled by imputation methods (Little and Rubin 2002).

Next, it is crucial to investigate the underlying mechanisms that cause missing data, in particular, the relationships between missing and non-missing data, because the mechanisms dictate the choice of remedies to handle a dataset with missing values (Little and Rubin 2002). A seminal paper by Rubin (1976) characterised three types of missing data mechanisms, which are depicted in Figure 6-1. If missingness does not depend on both observed and non-observed values of the complete dataset, then the data are known as missing completely at random (MCAR). The second mechanism is a less restrictive case that denotes missingness which only depends on observed values of the dataset and is known as missing at random (MAR). Finally, if the distribution of the missing values depends on the missing values in the data matrix, then data are not missing at random (NMAR). Most remedies are suitable for MCAR and MAR mechanisms, but if the data are NMAR, the analysis will be biassed (Little and Rubin 2002). To identify the underlying mechanism behind missing data, two methods were employed.

Figure 6-1: Graphical representation of missing data mechanisms[25]



Source: Adopted from Schafer and Graham (2002 p.152)

First, t-test was conducted to examine the means between groups of missing and non-missing data. The results of the analysis can be found in Appendix 10. The pattern of significant t-values could be observed for a large number of variables, indicating the relationship between missing and non-missing values, making it of some concern.

The second test intended to check whether data were missing completely at random (MCAR) or not, by comparing if the observed pattern in the data differs from a random pattern. A statistically significant level with p-values above 0.05 will indicate that the data are MCAR. In this instance, the

[25] *X* represents variables that are completely observed, *Y* represents a variable that is partly missing, *Z* represents the component of the causes of missingness unrelated to *X* and *Y,* and *R* represents the missingness.

results of Little's MCAR test were as follow: Chi-Square = 1988.423, DF = 1906, Sig. = 0.092. As can be seen, the result showed significant statistical levels larger than 0.05 but smaller than 0.1, indicating that an MCAR underlying missing data process was weak. Hence, data was classified as MAR, which assumes that the probability of the observation to be missing depends on the observation itself (Schafer 1997).

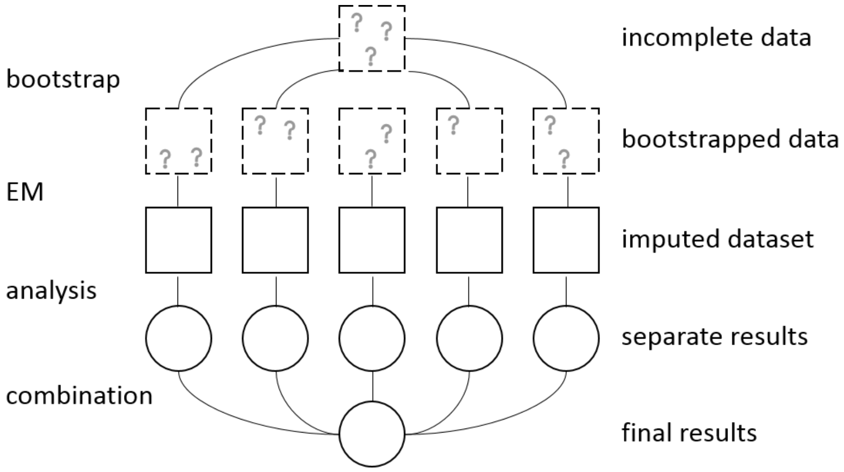
Summing up the results of diagnostic tests to find out the underlying randomness pattern of the missing data, the data were classified as MAR. When the data are not missing completely at random, it is not advisable to use methods such as listwise deletion of cases with missing values, weighting, averaging or use single imputation such as EM algorithm (Schafer and Graham 2002). In the case of MAR, a more advanced model-based multiple imputation technique needs to be used to input missing data for a complete dataset (Hair et al. 2010 p. 55), especially when dealing with secondary data as it allows to accommodate uncertainty about the missing data which the single imputation method such as EM does not offer (Wang et al. 1992).

Imputation & Treatment of Multiple Imputed Data

Multiple imputation (MI) procedure was carried out in R-Studio statistical software using version II of 'Amelia' package, which is built on ideas proposed by Honaker and King (2010) and enables to implement the imputation procedure as well as diagnose imputed values. Despite some level of inconvenience associated with working with multiple datasets instead of a more conventionally accepted one, multiple imputation helps to reduce bias produced by such methods as listwise deletion and mean imputation (Honaker et al. 2012).

Multiple imputation simulates *m* number of versions for each missing value in the dataset to account for uncertainty related to missing data (Honaker et al. 2012). MI can produce accurate estimates without many repetitions of simulations and typically m = 5 is sufficient (Schafer and Graham 2002). The computational method used in Amelia combines the classic EM algorithm with bootstrap technique (EMB) to take draws from the posterior model specification, which allows simulating estimation uncertainty, thereby improving the accuracy of imputation procedure, increasing efficiency and reducing bias (Honaker and King 2010). After imputation, any statistical method can be used to build and estimate models, and the results from *m* datasets are combined using specific commands designed for that or manually by applying formulas. The steps involved in imputation procedure are shown in Figure 6-2.

Figure 6-2: A schematic of multiple imputation approach using EMB algorithm



Source: Adopted from Honaker et al. (2012 p.6)

In addition to being classified as MAR, the data has to meet the multivariate normality assumption (Honaker et al. 2012). A preliminary visual check of outliers was carried out, as a result of that one case was deleted due to the presence of extreme values (case 141) which would distort the results of imputation, leaving a sample of 375 observations. The procedure also allows performing imputation-improving transformations of variables that do not meet the normality assumption. As a result, the imputation procedure was conducted twice–with original data and transformed data, whereby the most problematic variables were transformed into the logarithmic form. However, diagnostic tests, described in detail in the later section, demonstrated that untransformed data more closely fit the original data. Studies showed that Amelia tends to work well even for dichotomous or non-normal variables (King et al. 2001).

Considering that the estimation procedure is predictive in nature, it is important to include information on as many variables as possible in the imputation model to enhance its predictive power (Honaker et al. 2012). Thus, to increase the accuracy of the imputation model, data on all cases and variables were included in its original format, variables were categorised into nominal and ordinal scales, and upper and lower logical bounds were set to variables. When the data contain variables with great extent of missing values or intercorrelations, it is strongly recommended that a small ridge prior of up to 5% is included in the imputation model specification (Honaker et al. 2012). A ridge prior adds numerical stability by reducing covariates among the variables closer to zero, while leaving means or variances intact (Honaker et al. 2012). Following these recommendations, Amelia imputation code included 1% ridge prior. Finally, since data contained units that vary over time, a cross-sectional time-series option was specified to allow Amelia to add covariates to the model and create time index of polynomials, which allows cross-section units to change over time, thereby improving imputation procedure (Honaker et al. 2012). The imputation model converged normally and the imputation procedure generated five datasets.

After, two diagnostic tests—density plots and overimputation—were performed to assess the level of accuracy of imputed values. The first test was used to check the density plots of variables, which directly compare the distribution of imputed versus observed data (Honaker et al. 2012). The red line on the graph represents the density of the mean imputation across the five generated datasets, while the black line plots the density of observed data (Abayomi et al. 2008). Although the nature of multiple imputation procedure makes it impossible for distributions to be identical to the observed data, visual inspection of density plots is helpful to flag up any odd distributions that fall outside of set bounds (Honaker et al. 2012). The density plots can be seen in Appendix 11. For most variables, the imputed red lines followed the observed black lines relatively closely, while the distribution smoothened and lost prominent peaks. The only notable exception was the 'project duration' variable, for which the imputed distribution of values was quite different from original values.

The second diagnostic tool used was overimputation, which allows assessing the overall fit of the imputation model (Honaker et al. 2012). The technique handles observed data as if they were missing and imputes hundreds of values for each observed data point based on the initial imputation model, which subsequently enables to generate confidence intervals in order to inspect whether imputed data fit in the bounds of observed data (Honaker et al. 2012). The diagonal line on the overimputation diagnostic graph represents the true values, so the proximity of imputed values to the line is an indicator of the accuracy of the imputation model. The dots represent the mean imputation, the vertical lines represent the 90% confidence intervals for imputations of each observed value, and the colours of the lines depicted in the legend apply to the fraction of missing observations (Honaker et al. 2012). The graphs for metric variables shown in Appendix 12 demonstrated that confidence intervals contained the diagonal line (the true observed values) in the majority of cases, suggesting the robustness of the imputation model.

In addition to diagnostic tests, sensitivity analysis, shown in Appendix 13, was performed to compare original and imputed data. Means and standard deviations were calculated for all imputed variables across all five datasets and compared against the mean and the standard deviation of the original dataset. The difference in values of mean and standard deviation between the average across five datasets and the original dataset of more than 1 was believed to merit attention. One variable—namely, project duration—had a difference in both means and standard deviations of above the threshold of 1. As mentioned earlier, the density plot depicting project duration variable also showed that the line of imputed values did not follow the original line accurately. However, given that only 2, or 0.5% of cases were missing, such inaccuracy was not of concern. Manager's elite education and PI's citations variables had a difference in means of more than 1. However, since both variables had standard deviations below the threshold of 1, no concerns were raised. Although PI's citations variable had the highest difference in means, the fraction of missing values was only 2.1%, indicating that the variable will not be severely affected by the imprecision of imputation procedure.

Overall, both diagnostic and sensitivity analyses demonstrated that imputation procedure generated satisfactory results and none of the variables looked particularly troublesome, so imputed data can be safely used in subsequent stages.

Analyses described in the results chapter were carried out using the 'mi' command in STATA software package, which is designed to pool estimates obtained from 5 imputed datasets. The 'mi' procedure utilises formulas for combining multiple complete-data inferences described by Schafer (1997). The multiple-imputation regression coefficients are simply averaged, but variance estimation comprises within-imputation variance and between-imputation variance which produces more robust standard errors (Schafer 1997).

Outliers

Outliers are *"observations with a unique combination of characteristics identifiable as distinctly different from other observations"* (Hair et al. 2010 p.64). Such observations are usually characterised by extremely low or high values identified on a single variable or as a combination across a number of variables, which makes them stand out from other observations (Hair et al. 2010). Outliers which are observations unrepresentative of the population may distort the results, and thus often need to be excluded, yet the influence of each case merits context-specific assessment (Hair et al. 2010). Detection of outliers was conducted using univariate, multivariate and visual inspection tools described in detail below.

Univariate Detection of Outliers

The univariate identification method compares variables after the data have been standardised to have a mean of 0 and standard deviation of 1 and cases which are outside of the range of the distribution are considered as outliers (Hair et al. 2010). As a rule of thumb, if the sample size is larger than 80 cases, a case is considered an outlier if its standard score is ±4.0 or if it falls outside the range of 4 standard deviations (Hair et al. 2010 p.67).

Data were standardised in SPSS and obtained z-scores were analysed variable by variable to determine problematic cases. Appendix 14 shows potential candidates for deletion, sorted by the frequency of occurrence of z-scores above or below the recommended value of 4 in corresponding variables. There were 4 cases identified as potential candidates for deletion as each affected over 10 variables (cases 153, 152, 151 and 150) and other 7 required further consideration as they affected between 3 to 8 variables (cases 294, 268, 337, 282, 295, 115, 225, 188).

Multivariate Detection of Outliers

Although univariate and bivariate methods are useful as a starting point in outlier detection, they are limited in their ability to examine a combination of several variables, which is essential in multivariate analysis (Hair et al. 2010). Mahalanobis D^2 statistic addresses this problem by measuring the multidimensional position of each observation across a set of variables as the distance of each observation from the mean centre of all observations (Hair et al. 2010). However, this metric only provides the overall evaluation of each case but gives no further detail on which variables contain problematic cases, which indicates complementarity of all methods of outlier detection (Hair et al. 2010).

Mahalanobis D^2 measure was calculated in SPSS by adding all metric independent variables to a linear regression model and setting firm age as an arbitrary dependent variable. Then, for interpretation purposes, obtained Mahalanobis D^2 values were divided by degrees of freedom. In large samples of over 100 observations, the threshold value of the D^2/df statistic is between 3 and 4. With this threshold, as Appendix 15 shows, four cases 225, 337, 268 and 153 were identified as significantly different based on their frequency of occurrence across all imputed datasets. However, only cases 337, 268 and 153 that appeared in the multivariate outlier detection test were also identified as problematic in univariate and visual analyses. As a result, the identification of case 225 through multivariate analysis was interpreted as not worthy of concern, as this case is not unique on any single variable but instead is unique in combination.

Visual Detection of Outliers

Additionally, box plots were used to visually inspect variables for the presence of outliers. The results of visual outlier detection analysis have identified a number of extraordinary observations, presented in Appendix 16. Appendix 17 presents the summary of the visual analysis, which located several extreme cases affecting specific variables as potential candidates for deletion.

To assess whether any of the problematic cases identified during univariate, multivariate or visual inspection should be deleted, the decision was based on the main inclusion criteria that were used to construct the initial sample. That is, in the present empirical setting, the main eligibility criterion for firms to participate in the SBIR programme is that their total size does not exceed 500 employees. Therefore, the extreme case 77 identified in employment performance variable was kept in the dataset as it does not exceed the threshold of 500 employees. The extreme case 268 identified in sales performance variable, however, despite fitting the size criterion, was recognised as problematic across all three detection tests. Additionally, two outliers, cases 89 and 304 seemed to severely affect initial commitment (project-level) variable. Although the results of the box plot visual analysis revealed a number of outlying values, because they were not identified as problematic in other analyses and because they were believed to fit the selection criteria and the objectives of the research project, they were kept in the dataset.

To conclude, sensitivity analyses were performed with and without identified problematic 8 outliers, namely cases 89, 150, 151, 152, 153, 268, 304 and 337 to see if they affect the results. Consequently, it was concluded that their presence inflates statistical effects, as a result of which they were deleted as significant outliers, leaving a working sample of 367 observations.

6.3 Assumptions of Multivariate Analysis

While the earlier stages involved cleaning data for a workable format, the last stage in preparing data requires testing assumptions that underlie the statistical bases for multivariate analysis (Hair et al. 2010). Although inferences and results of some statistical techniques are prone to violations in these assumptions, it is still important to meet some of the assumptions to guarantee robustness of the estimation procedure and to understand any potential implications that they may have on the interpretation of the results (Hair et al. 2010). Four main assumptions, namely normality, multicollinearity, linearity and homoscedasticity that have an impact on every univariate and multivariate statistical method, are investigated in detail in the following sections.

Normality and Transformations

Normality, one of the most crucial assumptions of statistical theory, is concerned with comparing the shape of the data distribution for every variable measured on a continuous scale against the normal distribution (Hair et al. 2010). Even though larger sample sizes minimise the negative effects of nonnormality of data, it is essential to investigate univariate normality as any large deviation from the normal distribution will result in biassed estimates of statistical tests (Hair et al. 2010). The shape of the data distribution is assessed in terms of two measures–kurtosis and skewness. While the former reflects the height of the distribution, the latter refers to its centrality or symmetry (Hair et al. 2010).

Testing of normality assumptions tends to start with the basic visual examination of data using histograms and normal probability Q-Q plots which depict how close data are to a normal distribution. Obtained normal probability plots demonstrated departures of plotted data values from the straight diagonal line, while histograms showed a significant number of skewed variables, indicating nonnormality (Appendix 18).

Although graphical examination of normality is useful, it does not tell by how much the data deviate from the normal distribution. To address this, statistical tests can be used to calculate the z values of kurtosis and skewness that underpin normality assumptions. Under symmetrical distribution, skewness value is zero or lies between -1 and +1, while kurtosis is expected to have a value of 3 (StataCorp 2013). Therefore, values of skewness and kurtosis that exceed this threshold, indicate departures from normality. However, Kline (2011) suggested that variables with skewness score of above 3 are considered extremely problematic, while kurtosis score in the range from 8 to 20 indicates an extreme case.

Skewness and kurtosis scores for metric variables were calculated in STATA[26]. As can be seen from Table 6-1 skewness and kurtosis scores were above the proposed critical values, indicating that majority of variables lacked symmetry, and had peaked and right-tailed observed distribution.

To mitigate the effect of positively skewed and peaked distributions, data can be transformed by applying the power function, of which logarithm is the most widely used form (Hair et al. 2010; Cohen et al. 2003). A logarithm is a nonlinear mathematical transformation that changes the relative spacing of scores on a scale (Cohen et al. 2003 p.253). For cases with severe positive skewness the logarithmic transformation with a higher base, such as $\log_{10}$ is a recommended remedy over the natural log transformation ln, or $\log_{e,}$ which is more suitable for less severe cases (Kline 2011 p.63). Given that some variables had zero values which have a theoretical meaning, in order to keep all observations after the logarithmic transformation, it is advisable to add a small arbitrary constant to all values so that the lowest value is 1 (Kline 2011). Such remedy, referred to in the literature as 'started logs' or 'started powers' (Cohen et al. 2003 p.235), was originally proposed by Mosteller and Tukey (1977) and is frequently used in business studies, especially when using patent statistics (e.g. Andries and Faems 2013; Haeussler et al. 2014) or TMT backgrounds (e.g. Tornikoski and Newbert 2007) of nascent firms.

As a result, the transformation of $\log_{10}(1+x)$ was chosen as the most optimal type of remedy and was applied to all variables to see if it improves skewness and kurtosis scores. The transformation did not improve the distribution of data for variables which had minimal deviations from ideal scores of skewness and kurtosis. Therefore, such variables were kept in their original format. The last two columns on the right-hand side of Table 6-1 report improved scores after the transformation was applied. To sum up, all variables used for subsequent analyses, had skewness values below 3 and

[26] STATA uses a formula by Bock (1975) to calculate the value of kurtosis which adds a constant of 3 to the score. Klein, however, uses the formula by Snedecor and Cochran (1967) which calculates the kurtosis in the same way, but does not add the constant of 3. Therefore, critical values proposed by Kline can be increased by 3 to account for differences in formulas.

kurtosis values below 8—the recommended thresholds—implying that normality assumption was met.

Table 6-1: Skewness and kurtosis statistics of metric variables before and after transformations

Variable	Before Transformation		After Transformation	
	Skewness	Kurtosis	Skewness	Kurtosis
Sales performance	3.400	15.349	1.530	4.609
Employment performance	4.597	35.873	0.742	3.062
Innovation performance	6.552	63.115	1.217	4.032
Sales yield	7.107	60.793	1.740	6.421
Employment yield	8.037	87.512	0.663	3.186
Innovation yield	6.092	53.435	1.587	4.716
Initial commitment (project)	2.280	10.563	1.883	7.955
Initial commitment (portfolio)	2.206	11.062	1.589	7.263
Sequencing	1.853	7.518	1.228	3.927
Manager’s firm tenure	1.673	6.534	-	-
PI’s firm tenure	1.476	5.199	-	-
Manager’s technical experience	0.478	2.347	-	-
PI’s technical experience	0.505	2.892	-	-
Manager’s entrepreneurial experience	1.228	4.476	-	-
PI’s entrepreneurial experience	1.570	5.376	-	-
Manager’s commercial experience	0.510	2.546	-	-
Manager’s elite education	0.721	2.706	-	-
PI’s elite education	0.794	3.109	-	-
Manager’s patents	4.290	29.434	0.663	2.393
PI’s patents	6.652	57.125	0.794	3.346
Manager’s publications	2.946	14.533	-0.075	1.725
PI’s publications	2.230	8.187	-0.383	2.896
Abstract readability	1.294	6.975	0.568	4.356
Project duration	0.593	2.464	-	-
Invention activity	4.154	25.883	0.908	2.993
R&D capability	0.307	3.093	-	-
Managerial capability	1.357	3.919	-	-
Intellectual capability	0.347	4.102	-	-
State innovativeness	-1.191	3.817	-	-
Industry volatility (2014)	-1.495	4.059	-	-
Industry volatility (t)	1.033	4.077	-	-
Firm age	1.534	5.329	-0.240	2.606

Linearity

Another critical assumption to check is that correlational measures, which form the basis for all multivariate analyses, present the linear association (Hair et al. 2010). Linearity represents the change in the dependent variable for each unit increase in the independent variable, and if such association is nonlinear in nature, the strength of the relationships will be underestimated, undermining the predictive power of the multivariate model and estimated parameters (Hair et al. 2010).

The most widely used methods to determine whether the variables show a curvilinear relationship is to either visually examine scatterplots of the pairs of metric variables or the residual plots of the dependent variable after every regression equation. If the results depict the violation of the assumption, to achieve linearity, the most common remedy is to transform the variables by adding polynomial terms.

Linearity assumption was tested using a visual examination of augmented component-plus-residual plots in STATA using the 'acprplot' command. The method was initially proposed by Mallows (1986) and is known to be sensitive to identifying nonlinearity as it enables examination of the functional form of the data because of its ability to present multidimensional data in a two-dimensional format. Residuals for all metric variables are obtained in the regression analysis and then the regression line takes a slope equal to the estimated coefficient of the independent variable in the original regression model. All graphs include a median spline to assist visual interpretation of how closely the regression line fits the data. The plots were generated for every regressor in each equation and can be seen in Appendix 19. The lines in some plots appeared curvilinear; however, upon closer inspection, it became apparent that such effect was driven by a few outliers in the data. As a result, it was concluded that the plots did not exhibit any significant deviations from the linearity assumption. Hence, no remedies were necessary.

Homoscedasticity

The next important test relates to the dependence relationships, as expressed by the constant variance of individual variables or their combination (Wetherill 1986). This assumption relates to homoscedasticity and is essential so that dependent variables display a relatively equal degree of variance across all explanatory variables (Hair et al. 2010 p.74). The case when the variance of the dependent variable is determined by only a few explanatory variables, indicating that conditional spread of dispersion is not constant and non-linear, is known as heteroscedasticity (Chatfield 1995). The presence of heteroscedasticity is related to increased predictive power of certain relationships incorporated in the multivariate model and, although parameter estimates will remain unbiased, it may undermine the accuracy of the standard errors and interpretation of hypothesis tests (Hair et al. 2010). Heteroscedasticity may be a result of the presence of types of variables which either have an inherent propensity towards dispersion, such as percentages or variables with a broad range of increasing values, or have a skewed distribution (Hair et al. 2010).

In multiple regression, it is important to examine the effect of the linear combination of independent variables in explaining the dependent variable collectively, which can be assessed through the derived variate of the estimated regression model. The error of the variate is estimated as the difference between observed and predicted, or fitted values for the dependent variable, and the homoscedasticity assumption can be tested by plotting and examining the pattern of the error term, also known as the residual (Hair et al. 2010 p.183).

To examine whether the error term exhibits the constant variance, residuals were plotted against the fitted dependent value and compared to the null plot to see the pattern. When all the assumptions are met, the pattern should resemble the null plot, in which the residuals are distributed randomly, relatively equally around the zero line and with no prominent tendencies towards either side (Hair et al. 2010 p.183). The plots shown in Appendix 20 further confirmed the above conclusion that that data met the linearity assumption. However, some plots depicted the pattern of variation in the residuals, indicating heteroscedasticity.

In addition to the visual inspection, Breusch-Pagan / Cook-Weisberg and White's tests for heteroscedasticity were carried out for each regression equation used in the model, which test the null hypotheses that the error variances are equally distributed, i.e. are homoscedastic. Whereas the former test can only detect linear forms of heteroscedasticity, the latter can also test for non-linear forms of heteroscedasticity and can relax the assumption that the residuals are normally distributed (Greene 2012). The results of Breusch-Pagan test summarised in Table 6-2[27] further supported the above conclusion that the data in the regression equations did not meet the homoscedasticity assumption, which was rejected at statistically significant probability levels. White's test, however, did not flag any violations of the homoscedasticity assumption.

The results of the visual inspection and one out of two statistical tests reveal that heteroscedasticity is present. Taking into consideration the fact that the variables had been already transformed, the best possible remedy to deal with the problem of heteroscedasticity is to estimate robust standard errors, which produce unbiased p-values in the presence of dependent and unequally distributed residual terms (Allison 1999). Hence, to avoid any potential misinterpretation of hypotheses tests, robust standard errors were reported after each regression model in the subsequent results chapters.

[27] Statistical methods are currently unable to test equations with binary dependent variables. Hence, the equation from the Signalling conceptual model with Discontinuation as dependent variable is not included in the table.

Table 6-2: Results of Breusch-Pagan/Cook-Weisberg and White's tests for heteroscedasticity

Model	Equation	Breusch-Pagan Test		White's Test	
		Chi^2	$Prob>Chi^2$	Chi^2	$Prob>Chi^2$
ROR	Sales Yield, no prior awards	20.45	0.0000	67.79	0.6811
	Sales Yield, with prior awards	43.17	0.0000	148.03	0.0696
	Employment Yield, no prior awards	7.31	0.0069	80.28	0.2889
	Employment Yield, with prior awards	4.25	0.0393	141.02	0.1407
	Innovation Yield, no prior awards	7.06	0.0079	90.24	0.0984
	Innovation Yield, with prior awards	59.50	0.0000	101.53	0.9306
	Sales Performance, no prior awards	45.01	0.0000	73.54	0.4931
	Sales Performance, with prior awards	30.54	0.0000	133.14	0.2712
	Employment Performance, no prior awards	12.28	0.0005	67.97	0.6753
	Employment Performance, with prior awards	6.62	0.0101	137.80	0.1873
	Innovation Performance, no prior awards	12.87	0.0003	83.06	0.2205
	Innovation Performance, with prior awards	23.84	0.0000	112.79	0.7554
Signalling	Initial Commitment, no prior awards	21.60	0.0000	128.00	0.4336
	Initial Commitment, with prior awards	47.77	0.0000	239.00	0.5061
ROR and Signalling	Sales Yield, no prior awards	16.35	0.0004	128.00	0.4584
	Sales Yield, with prior awards	70.02	0.0000	239.00	0.4696
	Employment Yield, no prior awards	1.65	0.1991	128.00	0.4584
	Employment Yield, with prior awards	7.84	0.0051	239.00	0.4696
	Innovation Yield, no prior awards	8.77	0.0031	128.00	0.4584
	Innovation Yield, with prior awards	42.81	0.0000	239.00	0.4696
	Sales Performance, no prior awards	53.19	0.0000	128.00	0.4584
	Sales Performance, with prior awards	18.67	0.0000	239.00	0.4696
	Employment Performance, no prior awards	8.66	0.0033	128.00	0.4584
	Employment Performance, with prior awards	1.66	0.1970	239.00	0.4696
	Innovation Performance, no prior awards	12.95	0.0003	128.00	0.4584
	Innovation Performance, with prior awards	36.49	0.0000	239.00	0.4696

Multicollinearity

The cases when two or more independent variables are strongly correlated are known as collinearity and multicollinearity, respectively (Cohen et al. 2003). High degree of intercorrelations between independent variables makes it problematic to interpret the extent to which any single independent variable explains variation in the dependent variable. Therefore, to ensure that the interpretation of the regression variate is not affected by the interrelationships between independent variables, it is necessary to identify whether multicollinearity is an issue. The most obvious starting point is to examine the correlation matrix. As a rule of thumb, if the variables have a correlation of 0.9 or higher, that indicates collinearity. However, as a precautionary measure, it is advisable to pay attention even to bivariate relationships that have a correlation of 0.7 and higher (Hair et al. 2010).

Correlation matrix can only identify bivariate collinearity in a pair of variables, but is unable to assess the combined impact of a set of independent variables on a single independent variable. To establish whether multicollinearity might be present, the variance inflator factor (VIF) can be measured. High values of the VIF statistic indicate the high impact of the multicollinearity on the estimation procedure, including R^2 and regression coefficients. Hair et al. (2010) proposed a threshold of the VIF value of 10 which indicates substantive multicollinearity levels. However, the extant literature on statistics recommends that even variables with the VIF between 3 and 5 should be given careful attention.

Condition index (CI) is another useful metric to determine the extent of multicollinearity. As a rule of thumb, the condition index of 15 signifies multicollinearity, while the condition index of over 30 implies a severe problem (StataCorp 2013). Taking into account that multicollinearity is the data-related problem, the most logical remedy is to re-specify the model by omitting highly collinear variables. However, this solution may result in the specification error.

Diagnosis of collinearity was carried out by examining the bivariate correlations (reported later in Table 6-20) and the VIF statistics. Initial results of the correlation matrix revealed that manager's firm tenure is highly correlated with firm age. As a result, it was necessary to omit this independent variable from all equations comprising conceptual model. The VIF statistics were obtained by running the 'collin' command in STATA after each regression equation used in the conceptual model. The first run of collinearity diagnostics revealed that the Condition Index is above 100 which indicates a potential collinearity, although VIF statistics were all well below 5, with the average of less than 2. Given that the VIF does not show which variables are correlated or are causing the problem, an extension analysis was carried out using the 'coldiag2' command in STATA, which allows diagnosing condition indexes and variance-decomposition proportions of individual independent variables. The results of the latter test revealed that the collinearity problem was associated with the constant term, and its presence was inflating the overall condition index. Since the constant has no theoretical meaning in the present model, it was decided that it can be safely excluded from the diagnosis of multicollinearity. Therefore, multicollinearity was performed on the equations exclusive of the constant term, or intercept. The summary of results is depicted in Table 6-3, while more detailed results can be found in Appendix 21. The statistics were within acceptable limits, with the mean VIF of 1.8 and CI of 5, indicating that multicollinearity was not a problem.

Table 6-3: Summary of multicollinearity diagnostics

Model	Equation	Mean VIF	Condition Number
Signalling	Initial Commitment	1.84	5.1685
	Discontinuation	1.88	5.2159
ROR and Signalling	Sales Yield	1.86	5.2830
	Employment Yield	1.88	5.3443
	Innovation Yield	1.79	5.2754
	Sales Performance	1.85	5.1361
	Employment Performance	1.86	5.1384
	Innovation Performance	1.79	5.1379

Endogeneity

Following Shaver's (1998) seminal work on the role of endogeneity in affecting statistical findings, there has been a call in strategic management field to reduce the potential detrimental effects of endogeneity by using appropriate techniques (e.g. Bascle 2008; Hamilton and Nickerson 2003). Endogeneity is the term used to refer to the situation when an independent variable in an ordinary least-squares (OLS) regression is correlated with the residual (Kennedy 2003). Under such situation, error terms do not vary randomly, which violates the main assumption necessary for efficient estimation under the OLS regression model (Kennedy 2003). Erroneous inclusion of the correlation between the independent variable and residuals results in the estimation of biassed coefficients for relationships in the OLS model (Semadeni et al. 2014). Econometric literature identified four potential sources of endogeneity in OLS models: measurement error, autoregression, omitted variables and simultaneous causality (Kennedy 2003). Considering that endogeneity may bias the parameter estimates and interpretation of statistical inference tests, endogeneity should be explicitly investigated (Semadeni et al. 2014). Two most widely used remedies for endogeneity are the instrumental variables and the two-stage least square (2SLS) models, often used interchangeably (Semadeni et al. 2014). The instrument is a variable which is correlated with the endogenous variable but is exogenous to the model, and 2SLS is the technique to estimate instrumental variables regression model.

In line with the analytical road map proposed by Bascle (2008), the initial stage in examining the endogeneity problem is to identify whether it is even relevant in the given study. First, it is necessary to check whether OLS or 2SLS produces more consistent and robust estimates. Therefore, a specification test needs to be conducted to investigate the underlying assumptions of these two techniques (Wooldridge 2010). If the underlying assumption is that all explanatory variables are exogenous, then it is possible to allow one or more variable to be endogenous as an alternative assumption in order to test the difference between OLS and 2SLS (Wooldridge 2010).

Regression-based endogeneity tests offer convenience and ease of computation by directly comparing 2SLS and OLS, with Hausman statistic (Hausman 1978) being the most widely used test for the appropriateness of the random effects specification (Wooldridge 2010; Kennedy 2003). Investigation of whether some explanatory variables are endogenous was tested using the Durbin-Wu-Hausman test, which is based on the difference between 2SLS and OLS, and is carried out in several steps (Wooldridge 2010).

In the equation $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \alpha_1 z_1 + u_1$ there is an assumption that z_1 and u_1 might be correlated. Then, instruments x_3, x_4, x_5 are identified for z_1 and z_1 is regressed on all x variables to obtain the residuals v_2 from the reduced form OLS equation. Finally, v_2 is included in the initial OLS equation in order to get the t-statistic on v_2. If the p-value is at 10% significance level, then 2SLS may be a good alternative; if the p-value is 10% or more, then the null hypotheses that z_1 is exogenous cannot be rejected and OLS is deemed robust (Wooldridge 2010).

Endogeneity was hypothesised to be possible for two reasons. Empirically, a number of theoretically relevant variables were omitted from the model as they were causing multicollinearity. Theoretically, there might exist selection bias as a result of government venture funders' favouritism towards certain types of firms. As a number of authors cautioned, receiving government subsidies may be endogenous to a firm's R&D activities (Wallsten 2000) or their prospects for commercialisation (Link and Ruhm 2009). Both possibilities indicate that endogeneity may be associated with the reverse causality problem (Brander et al. 2014), as a result of which fixed effects models may overestimate the degree to which external funding causes improvements in performance.

To estimate the effect of potential endogeneity problem, the instrumental variables approach was used. Specifically, the assumption was that Phase I and Phase II funding outcomes, namely initial commitment and discontinuation variables might be endogenous as they can be influenced by unobservable selection effects. The major difficulty in using such approach is in identifying valid instruments. Relevant instruments were identified among the omitted variables, which were correlated with the hypothesised endogenous variables but were unrelated to the dependent variables. Two types of instruments were selected, which related to the availability of government funding (measured by the total budget, applications received and grants awarded) and the quality of firms' patenting. Then, the procedure described above was performed on all equations of the combined ROR and signalling model (Part III) using relevant selected instruments to arrive at the Hausman test statistic.

Table 6-4: Summary of results of the Hausman test[28]

Equation	Initial Commitment		Discontinuation[29]	
	F-value	Prob>F	F-value	Prob>F
Sales Yield, full sample	1.33	0.2541	0.16	0.6938
Sales Yield, no prior awards	0.04	0.8424	0.00	0.9556
Sales Yield, with prior awards	4.86	**0.0324**	3.03	**0.0854**
Employment Yield, full sample	0.58	0.4492	0.42	0.5236
Employment Yield, no prior awards	0.39	0.5385	0.56	0.4594
Employment Yield, with prior awards	1.40	0.2386	1.23	0.2691
Innovation Yield, full sample	0.03	0.8584	0.03	0.8610
Innovation Yield, no prior awards	0.15	0.7043	0.99	0.3229
Innovation Yield, with prior awards	0.91	0.3425	0.02	0.8800
Sales Performance, full sample	0.22	0.6442	0.23	0.6309

[28] The tests were performed on pooled multiply imputed datasets using the 'mi' command in STATA.
[29] For the results reported in the table, the first stage estimation was carried out using the Probit model as it produces more efficient estimates for binary variables, such as in the case of the hypothesised endogenous discontinuation variable. For robustness, for the binary endogenous variable, the first stage tests were also conducted using OLS which produced results consistent with the Probit procedure.

Sales Performance, no prior awards	0.88	0.3619	0.45	0.5118
Sales Performance, with prior awards	0.18	0.6691	0.18	0.6724
Employment Performance, full sample	0.07	0.7900	0.08	0.7767
Employment Performance, no prior awards	1.40	0.2479	1.45	0.2397
Employment Performance, with prior awards	0.47	0.4961	0.43	0.5145
Innovation Performance, full sample	1.05	0.3074	0.54	0.4620
Innovation Performance, no prior awards	0.03	0.8549	0.66	0.4206
Innovation Performance, with prior awards	0.24	0.6274	0.00	0.9695

The results in Table 6-4 show that only one of all tested equations may have a potential endogeneity problem: the null hypothesis that the hypothesised independent variable is exogenous was rejected for initial commitment equation at 5% significance level and discontinuation at 10% significance level. However, while the test on the full sample indicated no potential problem, it was concluded that endogeneity has little effect on the main estimates. Therefore, the use of the random effects model (2SLS) as an alternative method to the fixed effects model (OLS) to produce more efficient estimates, did not merit further attention. To conclude, although the Hausman test procedure did not find evidence that endogeneity may bias the estimates, the issue remains potentially relevant.

6.4 Summary of Constructs

To assist with the interpretation of subsequent descriptive and correlation analyses, the current section presents a series of tables (Table 6-5, Table 6-6, Table 6-7 and Table 6-8) summarising constructs used in the study: their operationalisations, measures and sources that were discussed in greater detail in the Research Methodology chapter as well as transformations that were applied as a result of testing of multivariate assumptions.

Table 6-5: Summary of dependent variables

Variable	Operationalisation	Source	Transformation
Sales Performance	Firm sales in t_{2014}, $ million	Hoover's Online	$\log_{10}(1+x)$
Employment Performance	Number of employees in t_{2014}	Hoover's Online	$\log_{10}(1+x)$
Innovation Performance	Patents application stock in the period from t until t_{2014}	Patbase & Espacenet	$\log_{10}(1+x)$
Sales Yield	$Sales_{2014}$ / $\sum_{t,\, t-1 \ldots t-n}$ Total Prior Investment	Hoover's Online, SBIR data	$\log_{10}(1+x)$
Employment Yield	$Employees_{2014}$ / $\sum_{t,\, t-1 \ldots t-n}$ Total Prior Investment	Hoover's Online, SBIR data	$\log_{10}(1+x)$
Innovation Yield	Patent applications $_{t,\, t+1, \ldots t2014}$/ $\sum_{t,\, t-1 \ldots t-n}$ Total Prior Investment	Patbase & Espacenet, SBIR data	$\log_{10}(1+x)$

Table 6-6: Summary of independent variables – real options reasoning constructs

Theoretical Construct	Definition	Level of Analysis	Independent Variable	Operationalisation	Measurement	Timing	Source	Transformation
Initial commitment (project-level funding)	Organisational commitment to projects at the point of initial resource allocation (Klingebiel and Adner 2015)	Project	Initial commitment (project-level)	Success magnitude: $ amount of Phase I award granted to an individual project in the database	Number retrieved from the SBIR database	t	SBIR data	$\log_{10}(1+x)$
Discontinuation (project-level funding)	Resource reallocation, or the reassignment over time of resources from deteriorating projects to more promising ones (Adner 2007)	Project	Discontinuation (project-level)	Phase II outcome: whether or not Phase I project in the database later received Phase II funding, dummy	Coding: Discontinue = 1 Continue = 0	t+n	SBIR data	none
Fit (project-level funding)	Consistency of resource allocation decisions (Klingebiel and Adner 2015; Adner 2007)	Project	Fit of funding decisions (project-level)	Fit is an interaction of initial commitment and reallocation. Low initial commitment: <mean High initial commitment:- >=mean	Coding: Low initial commitment x Discontinue / High initial commitment x Continue = 1 (fit) High initial commitment x Continue / Low initial commitment x Discontinue = 0 (no-fit)	t, t+n	SBIR data	none
Initial commitment (portfolio-level funding)	Same as above	Portfolio	Initial commitment (portfolio-level)	Average $ amount the firm received for cumulated prior Phase I awards	E.g., if the firm received a total of $0.75 million for 7 Phase I awards, then average prior Phase I $ award is 0.75/7=0.11	t-1	SBIR data	$\log_{10}(1+x)$
Sequencing (portfolio-level funding)	Continuous allocation of project resources over several steps (Tong and Reuer 2007)	Portfolio	Sequencing (portfolio-level)	Phase II transition rate: a ratio of a number of received Phase II awards per Phase I awards	E.g., if the firm received 2 Phase II awards and 10 Phase I awards, then the Phase II transition rate is 2/10=0.2	t-1	SBIR data	$\log_{10}(1+x)$
Fit (portfolio-level funding)	Same as above	Portfolio	Fit of funding decisions (portfolio-level)	Fit is an interaction of initial commitment and reallocation. Low initial commitment: <mean High initial commitment: >=mean Discontinue: Phase II transition rate = 0 Continue: Phase II transition rate > 0	Coding: Low initial commitment x Discontinue / High initial commitment x Continue = 1 (fit) High initial commitment x Continue / Low initial commitment x Discontinue = 0 (no-fit)	t-1	SBIR data	none

Table 6-7: Summary of independent variables – signalling constructs

Theoretical Construct	Level of Analysis	Independent Variable	Operationalisation	Measurement	Timing	Source	Transformation
Executive's functional role	Manager Principal investigator	Manager CEO PI CEO	Whether or not the person is a CEO, dummy	Coding: CEO = 1 Non-CEO = 0	t	LinkedIn	None
Organisational tenure	Principal investigator	PI's firm tenure	Tenure with the firm at the award date	Number of years, count	t	LinkedIn	None
Technical experience	Manager Principal investigator	Manager's technical experience PI's technical experience	Experience in technical positions in the same sector of the start-up before award date	Number of years, count	t-1	LinkedIn	None
Entrepreneurial experience	Manager Principal investigator	Manager's entrepreneurial experience PI's entrepreneurial experience	Entrepreneurial experience in any sector before award date	Number of years, count	t-1	LinkedIn	None
Elite Education	Manager Principal investigator	Manager' elite education PI's elite education	A score of the last attended university from the Top 100 worldwide universities ranking. Universities not in the top 100 received a score of zero	Scores retrieved from Academic Ranking of World Universities (ARWU)	t	Shanghai Ranking	None
Advanced business education	Manager Principal investigator	Manager's MBA PI's MBA	Whether or not the person has an MBA degree, dummy	Coding: MBA = 1 No MBA = 0	t	LinkedIn	None
Advanced technical education	Manager Principal investigator	Manager's PhD PI's PhD	Whether or not the person has a doctorate degree, dummy	Coding: Dr = 1 Mr/Ms = 0	t	LinkedIn	None
Academic seniority	Manager Principal investigator	Manager's professorship PI's professorship	Whether or not the person is a professor, dummy	Coding: Professor = 1 Not Professor = 0	t	LinkedIn	None
Inventive capacity	Manager Principal investigator	Manager's patents PI's patents	How many patent applications the person had prior to award date	Number of patent applications, count	t-1	Patbase	$\log_{10}(1+x)$
Academic competence	Manager Principal investigator	Manager's publications PI's publications	How many published documents the person had prior to award date	Number of published documents, count (includes journal articles, conference papers, books, and other, such as meeting, review, correction, clinical trial, editorial, and letter)	t-1	Scopus	$\log_{10}(1+x)$

Abstract readability	Project	Abstract readability	Gunning-Fog score (Fog Index) of the abstract provided in the Phase I project application	Readability measure: 0.4*(average number of words per sentence + percent of complex words). High values of the Fog Index imply less readable text.	t	SBIR data	$\log_{10}(1+x)$
Post-funding project duration	Firm	Project duration	How much time elapsed between Phase I project start and project end date	Number of days, count	t	SBIR data	None
Post-funding invention activity	Firm	Invention activity	How many patents applications the firm filed in a 3-year window following Phase I award	Number of patent applications from Patbase, count	t+1, t+2, t+3	Patbase	$\log_{10}(1+x)$
Project scope	Project	Project scope	Whether the project targets a specific cancer type or multiple	Coding: Multiple cancer types targeted = 1 (broad) Specific cancer type targeted = 0 (narrow)	t	SBIR data	None
Project category	Project	Federal program type	Federal programme type by assigned category from the Catalogue of Federal Domestic Assistance (CFDA)	Coding: Cancer Cause and Prevention Research = 1 Cancer Detection and Diagnosis Research = 2 Cancer Treatment Research = 3 Cancer Biology Research = 4	t	SBIR data	None
R&D capability	Firm	R&D capability	Technical efficiency of converting inputs into outputs	SFE Equation: Output (Invention Activity$_t$) = Input 1 (Quality-Adjusted Patenting Output) + Input 2 (Knowledge Breadth) + Input 3 (PI's Intellectual Capability)	t	SFA	None
Managerial capability	Manager	Managerial capability	Technical efficiency of converting inputs into outputs	SFE Equation: Output (Innovation Reach) = Input 1 (Commercial experience) + Input 2 (Intellectual Competence)	t	SFA	None
PI's Intellectual capability	Principal investigator	Intellectual capability	Technical efficiency of converting inputs into outputs	SFE Equation: Output (Academic Impact) = Input 1 (Quality-Adjusted Academic Competence) + Input 2 (Knowledge Appropriation) + Input 3 (Intellectual Competence)	t	SFA	None
R&D X Managerial capability	Firm & Manager	R&DCapXManCap	Interaction of R&D and managerial capabilities	Multiplication of mean-centred variables	t	SFA	None
R&D X Intellectual capability	Firm & Principal investigator	R&DCapXIntCap	Interaction of R&D and PI's intellectual capabilities	Multiplication of mean-centred variables	t	SFA	None
Intellectual X Managerial capability	Principal investigator & Manager	IntCapXManCap	Interaction of PI's intellectual and managerial capabilities	Multiplication of mean-centred variables	t	SFA	None

Table 6-8: Summary of control variables

Independent Variable	Level of Analysis	Operationalisation	Measurement	Timing	Source	Transformation
Non-woman-owned	Firm	Whether or not the firm is woman-owned, dummy	Coding: Non-woman-owned = 1 Woman-owned = 0	t	SBIR data	None
Non-minority-owned	Firm	Whether or not the firm is minority-owned, dummy	Coding: Non-minority-owned = 1 Minority-owned = 0	t	SBIR data	None
Non-HubZone-owned	Firm	Whether or not the firm is HubZone-owned, dummy	Coding: Non-HubZone-owned = 1 HubZone-owned = 0	t	SBIR data	None
Industry volatility (2014)	Environment	Industry volatility for a 5-year rolling window, lagged by 1 year	Industry stock return volatility computed as standard deviation from average annual equal-weighted returns of the Fama and French (1997) 49 industries	2013	Ken French Data Library	None
Industry volatility (t)	Environment	Industry volatility for a 5-year rolling window, lagged by 1 year	Industry stock return volatility computed as standard deviation from average annual equal-weighted returns of the Fama and French (1997) 49 industries	t-1	Ken French Data Library	None
State innovativeness	Environment	Innovation Scores of US States	The ranking list retrieved from Bloomberg's Visual Data platform	t	Bloomberg	None
Firm age	Firm	Firm age at project start	Number of years, count	t	Company website; Bloomberg Business Week	$\log_{10}(1+x)$
Project cohort	Project	Year of Phase I award, dummy	Coding: 2006 = 1 2007 = 2 2008 = 3 2009 = 4 2010 = 5 2011 = 6 2012 = 7	t	SBIR data	None

6.5 Descriptive Analysis

This section is designed to examine sample characteristics, distribution of individual variables as well as well their bivariate relationships, which is an important preliminary stage before embarking on more complex multivariate modelling. All relevant metrics and descriptive statistics were first averaged for each individual imputed dataset and then the results were pooled to arrive at the single average figure. Sample characteristics were expressed as counts and proportions of subgroups within the data; descriptive statistics encompassed central tendency, spread and range of data; bivariate relationships were analysed through the correlation matrix. For variables which underwent a transformation in order to normalise the data, statistics were reported before and after transformation. This was done because data before transformation provide more meaningful insights during the exploratory analysis, but it is also necessary to examine the data in the form that was used for regression analysis, that is, in a transformed form.

Sample Characteristics

As can be seen from Table 6-9, the sample was split into modelling scenarios to differentiate between the firms that had prior funding (239 cases) versus the ones that did not (128 cases).

Table 6-9: Summary of final sample and modelling scenarios

Sample	Sample Size	Definition
All cases	367	This sample includes all projects of firms
With no prior awards	128	This sample includes only projects in year *t* of firms that had no Phase I and Phase II awards prior to that year
With prior awards	239	This sample includes only projects in year *t* of firms that had Phase I and Phase II awards prior to that year

Table 6-10 shows that the final sample comprises 367 projects from 275 firms, 77% of these firms had 1 project in the sample, and the remaining 23% had more than 1 participating project. 37% of projects were conducted by young firms between 4-9 years old, and 29% of projects were performed by start-ups; only 18% of participating projects were from established firms. Project cohort refers to the year *t* in which the focal Phase I award was granted. A cohort of 2008 presents the highest proportion of participating projects in the sample, followed by 2007, and 2006. Total investment refers to U.S. dollar amount in millions received by each firm under the SBIR scheme as of year *t*. Nearly half of all participating projects (48%) are from firms that received up to $1 million worth of funding, 32% received more than $1 but less than $5 million, and the remaining 20% received over $5 million worth of SBIR awards.

Table 6-10: Descriptive characteristics of the sample – projects per firm, firm age, project cohorts and total SBIR investment

# of Projects per Firm	Count	%	Firm Age	Count	%	Project Cohort (t)	Count	%	Total SBIR Investment ($ million)	Count	%
1	213	77%	0-3	107	29%	2006	61	17%	0.10-0.99	177	48%
2	42	15%	4-9	137	37%	2007	79	22%	1.00-2.99	74	20%
3	15	5%	10-15	67	18%	2008	125	34%	3.00-4.99	44	12%
4+	5	2%	16-20	22	6%	2009	47	13%	5.00-6.99	15	4%
			21-40	34	9%	2010	48	13%	7.00-9.99	32	9%
						2011	6	2%	10.00-19.99	15	4%
						2012[30]	1	0%	20.00+	10	3%

The data displayed in Table 6-11 put firms into a wider environmental context. The majority of projects in the sample were run by firms registered in the state of California (23%), followed by Massachusetts (13%). Representation of firms from other states was quite small, yet almost equal (between 2% and 7%). Over half of all projects in the sample (53%) were conducted by firms primarily engaged in business services, which relates to research and development activities for commercial and non-commercial purposes. The second largest category of projects (17%) represented pharmaceutical industry, followed by medical equipment (6%). Whereas business services and medical equipment experienced quite volatile environments in 2013 and 2014, pharmaceutical products category was stable.

Table 6-11: Descriptive characteristics of the sample – location and industry

U.S. State	Count	%	Industry[31]	Count	%	Industry Volatility 2014 Rank	Industry Volatility 2013 Rank
CA	85	23%	Business Services	195	53%	8	4
MA	47	13%	Pharmaceutical Products	62	17%	10	11
TX	24	7%	Medical Equipment	21	6%	4	6
MD	22	6%	Computer Software	18	5%	1	1
NY	21	6%	Healthcare	16	4%	11	10
NC	15	4%	Wholesale	15	4%	5	5
WI	15	4%	Measuring and Control Equipment	11	3%	7	8
PA	14	4%	Construction	7	2%	2	3
CO	11	3%	Electronic Equipment	4	1%	9	2
WA	9	2%	Retail	3	1%	3	9
OH	9	2%	Construction Materials	1	0%	6	7
Other	95	26%	N/A	14	4%	N/A	N/A

[30] Although only 1 case was randomly drawn for the 2012 cohort, it was decided to keep it in the sample in order not to lose the data, although the dummy was omitted from regression-based models due to insufficient size of cases in the category.

[31] Ken French's classification was used - more detail on categorisation procedure was provided in the previous chapter.

Although all firms should qualify as a Small Business Concern (SBC) to be able to participate in the SBIR programme, some variation in size characteristics of applicants is apparent. As can be seen from Table 6-12, 64% of projects were conducted by firms with sales of up to $1 million, employing no more than 10 people. 31% of projects were from medium-sized firms with sales between $1 and $11 million and between 11 and 100 employees. Only around 5%-6% of projects were from large firms with sales of more than $11 million and over 100 employees. In a similar vein, firms' innovation activity corresponded to firms' size, with 64% of projects coming from firms with no more than 5 patent applications, followed by 33% of projects from firms with medium patenting activity between 6 and 60 patents, and only 4% of projects from heavily patenting firms.

Table 6-12: Descriptive characteristics of the sample – firm size and performance

2014 Sales ($ million)	Count	%	2014 Employees	Count	%	2014 Patent Stock[32]	Count	%
0.00-0.49	146	40%	1-5	149	41%	0	98	27%
0.50-0.99	89	24%	6-10	85	23%	1-5	135	37%
1.00-1.99	41	11%	11-20	56	15%	6-10	56	15%
2.00-2.99	21	6%	21-30	24	7%	11-15	24	7%
3.00-4.99	25	7%	31-40	11	3%	16-20	10	3%
5.00-10.99	23	6%	41-70	13	4%	21-30	18	5%
11.00-19.99	14	4%	71-100	10	3%	31-60	12	3%
20.00-30.00	8	2%	101+	19	5%	61-100+	14	4%

Descriptive Statistics of Performance Constructs

As can be observed from Table 6-13, the mean values of sales performance and employment performance are 2.46 and 19.95 respectively, which is in line with the insights drawn from the above table that the majority of firms were at the lower side of the size spectrum. The mean of innovation performance is 2.84, which refers to the average number of patent applications following funding allocation at Phase I. The means of yield measures are higher than the corresponding measures of actual performance, indicating that although the mean of total investment received is $3.39 million, majority of firms received smaller grants of under $1 million, which was also discussed in the previous sub-section. Standard deviations appear widely spread due to the large range between the minimum and maximum values, but transformation significantly improved the distribution of the data.

[32] Please note that the measure of innovation stock was only used in this section as an indicator of firm size, the measure of innovation performance used in subsequent analyses as a dependent variable denotes patent application flow, as opposed to the overall accumulated stock. For more detail, please refer to the research methodology chapter.

Table 6-13: Descriptive statistics of performance constructs

Variable	Before Transformation				After Transformation			
	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.
Sales Performance	0.0	27.7	2.46	4.93	0.00	1.46	0.34	0.35
Employment Performance	1	400	19.95	37.07	0.30	2.60	0.99	0.49
Innovation Performance	0	90	2.84	7.34	0.00	1.96	0.32	0.40
Sales Yield	0.0	108.3	3.31	10.63	0.00	2.04	0.36	0.37
Employment Yield	0.2	1200.0	30.25	89.32	0.06	3.08	1.01	0.58
Innovation Yield	0.0	133.3	3.94	11.65	0.00	2.13	0.31	0.46
Total Investment[33]	0.1	66.3	3.39	6.52				

Descriptive Statistics of Real Options Reasoning Constructs

The present sub-section explores variables used to measure ROR constructs. As seen from Table 6-14, the means of project-level and portfolio-level initial commitment are very similar, 0.18 and 0.10, respectively. The mean of sequencing is 0.21, which can be interpreted that on average for every 5 Phase I projects there is 1 Phase II project. Categorical variables are evenly represented between groups, although fit of funding decisions is less prevalent at the cumulated portfolio level than at the individual project level (43% versus 51% of cases). This statistic presents an important insight indicating that government venture funders implicitly follow ROR resource allocation logic in half the cases, which offers an opportunity to test empirically whether ROR investment pattern is associated with enhanced performance outcomes. The bottom part of Table 6-15 presents the alternative dummy operationalisations of selected variables, which were used for robustness checks only. On average two-thirds of observations fall in the ‘low’ category, while the remaining one-third falls in the ‘high’ category, which provides further confirmation that government venture funders implicitly follow ROR logic.

Table 6-14: Descriptive statistics of ROR constructs – metric variables

Variable	Before Transformation				After Transformation			
	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.
Initial Commitment (project-level)	0.06	0.75	0.18	0.09	0.03	0.24	0.07	0.03
Initial Commitment (portfolio-level)	0.00	0.86	0.10	0.12	0.00	0.27	0.04	0.04
Sequencing	0.00	2.00	0.21	0.30	0.00	0.48	0.07	0.09

[33] Total investment refers to U.S. dollar amount in millions received by each firm under the SBIR scheme as of year *t*. This variable was not included in subsequent analyses but is reported here because it was used as a denominator to calculate yield measures and hence provides useful insights.

Table 6-15: Descriptive statistics of ROR constructs – categorical variables

Discontinuation	Count	%	Fit (project-level)	Count	%	Fit (portfolio-level)	Count	%
Continue (0)	180	49%	No (0)	181	49%	No (0)	208	57%
Discontinue (1)	187	51%	Yes (1)	186	51%	Yes (1)	159	43%
Initial Commitment (project-level)	**Count**	**%**	**Initial Commitment (portfolio-level)[34]**	**Count**	**%**	**Sequencing**	**Count**	**%**
High (0)	139	38%	High (0)	74	31%	High (0)	65	27%
Low (1)	228	62%	Low (1)	165	69%	Low (1)	174	73%

Descriptive Statistics of Signalling Constructs

In comparison to managers, principal investigators had a higher mean technical experience (14.90 versus 16.90). On the contrary, managers had a higher mean entrepreneurial experience in comparison to principal investigators (6.90 versus 4.55). More managers appear to have attended elite educational institutions than principal investigators, as demonstrated by the means 29.62 and 26.58, respectively. Additionally, Table 6-16 shows that principal investigators had higher mean intellectual legitimacy, with a higher mean number of patents and publications in comparison to managers. Phase I project duration ranged from the minimum of 56 days to the maximum of 1096 days, with the average duration of 435 days. The mean of post Phase I invention activity is 2.79, with the maximum of 45 patent applications. The lowest score for abstract readability, which refers to the Fog Index, is 13.9, denoting projects with more readable text, while the highest score is 38.30. The mean readability score of 20.39 indicates that an average project was closer to the more readable end of the spectrum.

Capabilities were estimated using the stochastic frontier analysis (SFA) technique, which generates scores on a scale from 0 to 1. Therefore, efficiency scores can also be expressed as percentages, with the maximal 100% obtained by the most efficient firm. According to Table 6-16, all firms operated below the most efficient frontier of 1, with the maximum achieved efficiency scores of 0.42, 0.93 and 0.88 for R&D, managerial and intellectual capabilities, respectively. Managerial capability is the most widely dispersed measure of all three estimations, with the highest maximum of 0.93 and the lowest mean of 0.16, which may be attributed to the heterogeneity of managers' skills and strategic orientation. The highest mean of 0.34 for intellectual capability indicates that principal investigators are more efficient at transforming resources into a production output, than managers (0.16) or firms more generally (0.19). The fact that mean efficiencies are so low can be explained by the fact that 66% of projects in the sample were run by start-ups and young firms up to 10 year's old (Table 6-10), so technical efficiencies are still underdeveloped. Interactions of capabilities were mean-

[34] Average prior Phase I $ award and Phase II Transition Rate are only related to the cluster of firms with prior awards, hence the sample here is 239.

centred before being multiplied; as a result, these variables have a mean of exactly zero, although their frequency distribution remained unchanged.

Table 6-16: Descriptive statistics of signalling constructs – metric variables

Variable	Before Transformation				After Transformation			
	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.
PI's firm tenure	0	28	5.57	5.32				
Manager's technical experience	0	54	14.90	12.18				
PI's technical experience	0	50	16.90	9.82				
Manager's entrepreneurial experience	0	35	6.90	7.50				
PI's entrepreneurial experience	0	34	4.55	5.84				
Manager' elite education	0	100	29.62	28.70				
PI's elite education	0	100	26.58	25.60				
Manager's patents	0	61	3.71	6.67	0.00	1.79	0.42	0.44
PI's patents	0	162	5.61	14.40	0.00	2.21	0.50	0.46
Manager's publications	0	285	25.39	38.54	0.00	2.46	0.95	0.72
PI's publications	0	196	30.19	36.61	0.00	2.29	1.22	0.53
Project duration	56	1096	434.94	218.34				
Invention activity	0	45	2.79	5.43	0.00	1.66	0.36	0.40
Abstract readability	13.9	38.30	20.39	3.16	1.17	1.59	1.33	0.06
R&D capability	0.02	0.42	0.19	0.09				
Managerial capability	0.00	0.93	0.16	0.22				
Intellectual capability	0.00	0.88	0.34	0.16				
R&D X Managerial capability	-0.07	0.08	0.00	0.02				
R&D X Intellectual capability	-0.10	0.09	0.00	0.02				
Intellectual X Managerial capability	-0.10	0.29	0.00	0.04				

Table 6-17 provides further detail on signalling constructs which were operationalised as categorical variables. CEO variable is reversed, with 62% of managers having a leading position in comparison to 38% of principal investigators. The majority of members of the TMT did not hold an MBA degree, although managers presented a higher proportion of MBA holders, 17% in comparison to only 6% among principal investigators. On the contrary, 94% of principal investigators had doctorate degrees, compared to 64% among managers. The proportion of principal investigators holding a professorship was only marginally higher in comparison to managers, 33% versus 29%. The projects with narrow and broad project scope were almost proportionally represented, with most projects focused on cancer detection and diagnosis research (41%) and cancer treatment research (37%).

Table 6-17: Descriptive statistics of signalling constructs – categorical variables

Manager CEO	**Count**	**%**	**PI CEO**	**Count**	**%**
No (0)	141	38%	No (0)	226	62%
Yes (1)	226	62%	Yes (1)	141	38%
Manager' MBA	**Count**	**%**	**PI' MBA**	**Count**	**%**
No (0)	303	83%	No (0)	344	94%
Yes (1)	64	17%	Yes (1)	23	6%
Manager' PhD	**Count**	**%**	**PI's PhD**	**Count**	**%**
No (0)	133	36%	No (0)	24	6%
Yes (1)	234	64%	Yes (1)	343	94%
Manager's Professorship	**Count**	**%**	**PI's Professorship**	**Count**	**%**
No (0)	261	71%	No (0)	247	67%
Yes (1)	106	29%	Yes (1)	120	33%
Project Scope	**Count**	**%**	**Project Category**	**Count**	**%**
Narrow (0)	174	47%	Cancer Cause and Prevention Research (1)	48	13%
Broad (1)	194	53%	Cancer Detection and Diagnosis Research (2)	151	41%
			Cancer Treatment Research (3)	134	37%
			Cancer Biology Research (4)	34	9%

Descriptive Statistics of Controls

As is apparent from Table 6-18, the measure of industry volatility which refers to year *t* has a much wider range and dispersion in comparison to the measure of industry volatility which refers to year 2014. This is because year *t* includes multiple project cohorts as described in Table 6-10. The average firm age is 8.7 years, which is consistent with the discussion above. The mean of state innovativeness score is 67.55 and is relatively close to the maximum of 83.25. The reason behind this is that projects from California and Massachusetts, which make up 33% of the sample, represent the second and third most innovative states in the U.S. Representation of woman-, minority- and HubZone-owned firms is proportionally small, with 8%, 3% and 5% respectively, as seen from Table 6-19.

Table 6-18: Descriptive statistics of controls – metric variables

Variable	**Before Transformation**			
	Min	**Max**	**Mean**	**Std. Dev.**
Industry volatility (2014)	0.00	22.20	18.24	6.30
Industry volatility (t)	0.00	103.53	28.93	23.35
State innovativeness	20.95	83.25	67.55	15.50
Firm age	0	40	8.70	7.69

Table 6-19: Descriptive statistics of controls – categorical variables

Non-Woman-Owned	Count	%	Non-Minority-Owned	Count	%	Non-HubZone-Owned	Count	%
Yes (0)	28	8%	Yes (0)	12	3%	Yes (0)	17	5%
No (1)	339	92%	No (1)	355	97%	No (1)	350	95%

6.6 Correlation Analysis

Correlation coefficient *r*, invented by Pearson, is a standard measure of association between two variables (Cohen et al. 2003). It takes the value between -1 and +1 when one variable perfectly estimates another, with 0 suggesting no linear relationship. As such, the sign of the coefficients gives an indication of the tendency for a positive or negative increase in one variable as a result of an increase in another variable.

Correlation matrices are a widely used tool for discovering bivariate relationships between individual variables, both predictor-response and predictor-predictor pairs. Although the correlation matrix is merely a preliminary step before executing multivariate modelling, it offers significant insights on the directionality and the strength of effect sizes of the linear relationships between the variables (Cohen et al. 2003).

Multiple-imputation estimate of the correlation matrix was performed in STATA on the sample of 367 observations. To estimate the magnitude of effect sizes, correlations were compared with Cohen's (1992) guidelines: if $r < 0.30$, the effect size is considered small; if $0.30 < r < 0.50$, it is medium; and if $r > 0.50$, it is large. As Table 6-20 depicts, most effect sizes are small. However, dependent variables are highly intercorrelated, which further supports the use of the SUR modelling technique that accounts for interrelationships between variables.

The correlation matrix reveals a strong significant association between all ROR constructs except discontinuation and project-level fit, and dependent variables, validating the relevance of stated hypotheses. Both project-level and portfolio-level initial commitment, as well as sequencing, have a negative relationship with investment yield. On the other hand, portfolio-level initial commitment ($r = 0.11$ and $r = 0.14$) and sequencing ($r = 0.19$ and $r = 0.20$) have a positive association with sales and employment performance. The directionality of relationships is reversed for the portfolio-level fit, which is positively associated with investment yield and negatively associated with firm performance. As can be seen, fit measures are strongly correlated with the variables that were used to construct the interaction. However, as the VIF analysis demonstrated, such association did not cause multicollinearity.

Project-level and portfolio-level initial commitment have a significant positive association ($r = 0.25$, $p < 0.01$), suggesting funder's propensity for decision-making inertia. Similarly, portfolio-level initial commitment has a positive relationship with sequencing ($r = 0.25$, $p < 0.01$), which indicates that the magnitude of prior investment has an effect on the likelihood of later-stage funding continuation. Firm age has a positive association with portfolio-level initial commitment and sequencing ($r = 0.24$ and $r = 0.34$), and a strong negative association with portfolio-level fit ($r = -0.42$), which clearly indicates that matching of funding decisions in line with the ROR logic, gives younger candidates preferential access to capital.

The same pattern is evident from the association of portfolio level fit with TMT characteristics, with members with shorter tenure and less entrepreneurial experience having a favourable access to external funding under the ROR logic. Also, the implicit following of the ROR logic can be observed from the strong negative relationship between industry volatility and discontinuation ($r = -0.20$), implying that higher uncertainty increases the value of the option to 'hold'.

Relatively few of the hypothesised predictors have a significant association with dependent variables used in the signalling model (Part II). Manager's technical and entrepreneurial experience has a negative relationship with initial commitment ($r = -0.12$ and $r = -0.16$), whereas PI's CEO and professorship statuses have a negative association with discontinuation (each $r = -0.18$). Paradoxically, project duration has a medium-size positive association with both initial commitment and discontinuation ($r = 0.25$ and $r = 0.21$). This finding implies that firms that receive larger initial grants engage in longer experimentation; however, longer experimentation reduces the likelihood of receiving subsequent later-stage funding.

Firm age has a strong significant medium size relationship with sales and employment performance (each $r = 0.48$, $p < 0.01$), and a weaker relationship with innovation performance ($r = 0.13$). On the other hand, firm age is negatively associated with employment and innovation yield ($r = -0.15$ and $r = -0.20$). These findings suggest that as firms get more experienced, they become more successful, but present less lucrative targets for investment.

Post-funding invention activity has a strong positive association with innovation yield ($r = 0.43$, $p < 0.01$), sales ($r = 0.43$, $p < 0.01$), employment ($r = 0.44$, $p < 0.01$) and innovation performance ($r = 0.77$, $p < 0.01$). The latter large effect size indicates a potential multicollinearity problem since patent-based variables are tautological because of timing issues. As a result, to avoid possible confounding effects, post-funding invention activity was omitted as a predictor from equations where innovation yield and innovation performance measures are dependent variables.

Additionally, managerial capability has a strong positive association with sales ($r = 0.37$, $p < 0.01$), employment ($r = 0.41$, $p < 0.01$) and innovation performance ($r = 0.42$, $p < 0.01$), while other types of capabilities have a much weaker correlation, which suggests that managerial capability is an important intangible asset. All three capabilities have positive association with innovation yield and performance, indicating that heterogeneity of skills and competences is conducive to R&D success.

Managerial capability has a high effect size with post-funding invention activity ($r = 0.65$, $p < 0.01$). This is because managerial efficiency transformation function was expressed in terms of strategic change, or managers' ability to achieve higher innovation proliferation, measured by patents. Therefore, there is a strong association with the patent-based post-funding invention activity measure. However, the results of multicollinearity analysis carried out earlier confirmed that inclusion of both variables does not have a detrimental effect on regression models, hence both variables were kept in the equations as significant potential explanatory factors.

Industry volatility measured in year t has a large effect size with year dummies ($r = 0.70$, $p < 0.01$), which is not surprising as industry volatility relates to each project cohort and, hence, the same year. Among other relationships with large effect sizes that are worthy discussion are between PI's tenure and PI's entrepreneurial experience ($r = 0.65$, $p < 0.01$) and between manager's technical experience and entrepreneurial experience ($r = 0.59$, $p < 0.01$). The former relationship can be explained by the fact that many PIs are founders of firms in the sample; hence, their tenure with the firm is associated with their entrepreneurial experience. Similarly, other types of experience are intercorrelated because they tend to be accumulated simultaneously, though at different levels. Taking into account that the VIF and CI analysis in the earlier section confirmed that their joint presence in the regression model does not cause multicollinearity, it was decided that it is safe to keep them in the model.

6.7 Concluding Remarks

This chapter gave an account of empirical procedures carried out to prepare and investigate the data before the multivariate analyses. In particular, care was taken to make sure that data are complete, and that underlying assumptions are not violated. Additionally, insights into data were gained through descriptive and correlation analyses, setting the basis for subsequent regression modelling.

Table 6-20: Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(1)	Sales yield	1.00																						
(2)	Employment yield	**0.90**	1.00																					
(3)	Innovation yield	**0.38**	**0.38**	1.00																				
(4)	Sales perform.	**0.45**	**0.30**	0.10	1.00																			
(5)	Employment perform	**0.43**	**0.38**	0.10	**0.91**	1.00																		
(6)	Innovation perform.	**0.13**	0.06	**0.69**	**0.42**	**0.38**	1.00																	
(7)	Initial comm. (proj.)	**-0.18**	**-0.22**	-0.05	0.10	0.09	0.07	1.00																
(8)	Discontinuation (proj.)	-0.02	-0.02	-0.07	0.02	0.00	-0.05	-0.01	1.00															
(9)	Fit (project)	-0.01	-0.01	0.00	-0.08	-0.09	-0.04	-0.02	**0.24**	1.00														
(10)	Initial comm. (portf.)	**-0.35**	**-0.45**	**-0.19**	**0.11**	**0.14**	0.09	**0.25**	0.07	-0.05	1.00													
(11)	Sequencing (portf.)	**-0.35**	**-0.47**	**-0.24**	**0.19**	**0.20**	0.07	0.01	-0.07	-0.03	**0.25**	1.00												
(12)	Fit (portfolio)	**0.31**	**0.40**	**0.21**	**-0.24**	**-0.25**	-0.06	0.04	-0.02	-0.01	**-0.33**	**-0.52**	1.00											
(13)	Manager CEO	-0.07	-0.07	-0.07	**-0.31**	**-0.32**	**-0.16**	**-0.11**	-0.01	0.00	0.00	-0.08	0.09	1.00										
(14)	PI CEO	0.01	0.00	-0.06	**-0.17**	**-0.17**	**-0.14**	-0.07	**-0.18**	0.06	-0.04	0.01	0.02	**0.22**	1.00									
(15)	PI's firm tenure	**-0.13**	**-0.23**	**-0.18**	0.10	**0.11**	-0.02	-0.10	0.01	0.00	0.07	**0.29**	**-0.32**	-0.02	**0.20**	1.00								
(16)	Manager's tech. exp.	-0.03	-0.07	-0.06	-0.04	-0.06	0.02	**-0.12**	0.02	0.00	-0.03	0.10	-0.06	**0.28**	**0.11**	**0.27**	1.00							
(17)	PI's tech. exp.	-0.01	-0.03	-0.03	-0.04	-0.03	-0.02	0.03	-0.08	-0.01	-0.06	**0.12**	-0.04	0.08	**0.15**	**0.40**	**0.39**	1.00						
(18)	Manager's entrep. exp.	-0.01	-0.10	**-0.11**	0.06	0.03	0.03	**-0.16**	-0.01	-0.05	-0.01	**0.14**	**-0.16**	**0.33**	0.10	**0.38**	**0.59**	**0.23**	1.00					
(19)	PI's entrep. exp.	-0.03	**-0.11**	**-0.11**	-0.07	-0.05	-0.09	-0.09	-0.06	0.07	0.01	**0.17**	**-0.18**	**0.12**	**0.43**	**0.65**	**0.30**	**0.45**	**0.44**	1.00				
(20)	Manager's elite educ.	-0.02	-0.02	0.06	**0.23**	**0.24**	**0.26**	0.06	0.00	-0.04	0.05	0.10	**-0.13**	0.07	-0.09	0.00	0.02	-0.04	**0.19**	-0.02	1.00			
(21)	PI's elite educ.	0.03	0.07	0.06	0.01	0.07	0.04	-0.01	0.00	0.05	-0.04	0.00	-0.01	-0.09	0.08	0.02	**-0.20**	-0.01	**-0.16**	0.06	**0.35**	1.00		
(22)	Manager's MBA	**0.13**	**0.14**	**0.12**	-0.05	-0.03	-0.01	-0.07	-0.02	-0.06	-0.15	**-0.14**	0.05	-0.05	-0.08	-0.01	**-0.19**	-0.05	-0.02	-0.07	0.09	0.03	1.00	
(23)	PI's MBA	-0.07	-0.07	0.02	-0.10	**-0.11**	0.01	0.00	-0.09	0.02	-0.03	-0.08	0.04	0.02	-0.02	0.00	-0.01	-0.08	0.04	-0.03	0.10	0.00	**0.25**	1.00
(24)	Manager's PhD	-0.08	-0.05	-0.03	**-0.15**	**-0.15**	-0.09	-0.02	0.02	0.03	0.02	0.01	0.07	**0.22**	**0.14**	-0.01	**0.45**	0.03	0.10	0.06	-0.07	**-0.11**	**-0.37**	-0.09
(25)	PI's PhD	-0.06	-0.01	0.05	-0.02	0.01	0.09	0.06	0.03	-0.03	0.04	0.00	0.06	0.04	**-0.14**	**-0.11**	0.06	0.07	-0.10	**-0.19**	0.00	-0.02	-0.11	-0.09
(26)	Manager professor	-0.07	-0.07	-0.09	**-0.12**	**-0.11**	-0.10	-0.02	-0.10	0.02	-0.02	0.07	0.08	**0.25**	**0.14**	0.06	**0.41**	**0.14**	**0.24**	0.10	-0.03	-0.08	**-0.15**	-0.07
(27)	PI professor	-0.05	-0.03	-0.10	-0.01	0.01	-0.10	0.06	**-0.18**	-0.02	-0.04	0.10	0.00	0.04	0.09	**0.12**	**0.16**	**0.33**	0.06	**0.16**	-0.09	0.07	-0.06	-0.09
(28)	Manager's patents	-0.06	-0.09	-0.02	**-0.15**	**-0.12**	-0.01	-0.08	0.10	0.06	0.07	0.08	0.02	**0.28**	**0.16**	**0.13**	**0.39**	**0.17**	**0.20**	**0.17**	-0.02	-0.09	**-0.12**	-0.03
(29)	PI's patents	-0.02	-0.04	**0.13**	0.02	0.08	**0.23**	0.05	0.04	0.01	0.10	0.07	-0.09	-0.01	**0.16**	**0.18**	**0.15**	**0.32**	0.06	**0.25**	-0.06	0.03	-0.06	-0.09
(30)	Manager's publications	-0.08	-0.10	-0.08	-0.06	-0.08	-0.02	-0.07	-0.02	0.01	0.02	0.08	0.01	**0.24**	**0.14**	0.06	**0.59**	0.09	**0.28**	**0.11**	0.08	**-0.12**	**-0.28**	-0.07
(31)	PI's publications	-0.04	-0.03	**0.12**	0.03	0.06	**0.17**	-0.03	**-0.12**	0.01	0.04	0.09	-0.03	0.04	0.05	**0.12**	**0.23**	**0.47**	0.07	**0.14**	0.09	-0.01	-0.08	**-0.12**
(32)	Abstract readability	0.04	0.02	-0.01	0.01	-0.01	-0.05	0.01	-0.03	-0.06	-0.01	0.00	0.07	-0.04	**-0.11**	**-0.13**	-0.04	-0.02	-0.01	**-0.18**	**-0.14**	**-0.11**	0.00	-0.04
(33)	Project duration	**-0.17**	**-0.22**	**-0.11**	0.06	0.03	0.09	**0.25**	**0.21**	-0.04	**0.14**	0.07	-0.06	**-0.11**	**-0.17**	-0.04	-0.01	-0.03	-0.06	-0.07	0.02	-0.02	**-0.13**	-0.01
(34)	Invention activity	**0.11**	0.05	**0.43**	**0.43**	**0.44**	**0.77**	0.07	-0.04	-0.04	0.08	**0.16**	**-0.11**	**-0.24**	**-0.11**	0.09	-0.03	0.01	0.04	0.00	**0.28**	0.09	0.02	-0.04
(35)	R&D capability	0.08	**0.11**	**0.20**	0.08	**0.12**	**0.24**	0.09	0.00	0.05	0.01	-0.07	0.08	**-0.14**	-0.07	-0.08	**-0.14**	-0.08	**-0.17**	-0.10	0.10	0.06	0.06	**-0.11**
(36)	Managerial capability	**0.11**	0.07	**0.17**	**0.37**	**0.41**	**0.42**	**0.12**	0.06	0.01	0.09	0.10	**-0.12**	**-0.31**	**-0.12**	**0.13**	**-0.11**	0.07	0.00	0.03	**0.17**	0.01	0.04	-0.06
(37)	Intellectual capability	-0.07	-0.01	**0.13**	0.00	0.02	**0.15**	-0.05	0.01	0.01	-0.01	0.01	-0.01	-0.01	**-0.12**	-0.09	0.02	**-0.12**	-0.06	-0.08	0.05	0.01	-0.04	-0.05
(38)	Project scope	0.06	0.06	-0.04	0.04	0.07	-0.05	**-0.13**	-0.01	0.07	0.02	0.09	-0.09	-0.07	0.10	-0.02	-0.03	**-0.23**	0.08	0.01	0.04	**0.11**	-0.09	**-0.17**
(39)	Project category	0.02	0.02	0.03	-0.02	-0.02	0.05	0.10	**0.11**	0.00	0.03	-0.10	0.08	-0.06	-0.06	-0.09	0.03	-0.02	-0.09	**-0.11**	-0.01	-0.09	0.02	0.06
(40)	Non-woman-owned	0.07	0.07	0.06	0.09	**0.13**	**0.11**	0.05	0.07	-0.02	0.05	-0.03	0.02	-0.03	**-0.13**	-0.08	0.04	-0.04	-0.05	**-0.13**	0.12	0.01	0.00	0.03
(41)	Non-minority-owned	0.00	-0.03	0.08	0.02	0.02	**0.11**	0.04	-0.03	-0.03	0.04	0.03	0.04	**-0.15**	-0.05	-0.08	-0.03	-0.09	-0.03	**-0.12**	0.04	-0.05	0.07	0.03
(42)	Non-HubZone-owned	-0.09	**-0.11**	-0.04	0.01	0.01	0.02	-0.05	0.04	0.04	0.07	0.08	-0.07	0.09	**-0.13**	0.05	0.03	-0.04	0.05	0.01	0.01	**-0.11**	0.00	-0.04
(43)	Industry volatility (2014)	**-0.19**	**-0.13**	0.03	-0.03	0.03	0.08	**0.15**	0.06	0.01	**0.14**	0.04	-0.04	-0.09	**-0.15**	-0.10	-0.09	-0.02	**-0.25**	**-0.11**	0.04	0.03	-0.03	0.02
(44)	Industry volatility (t)	-0.10	-0.08	-0.04	-0.07	-0.08	-0.08	**0.13**	**-0.20**	0.03	0.06	-0.02	0.08	-0.03	-0.01	-0.03	-0.04	-0.03	**-0.12**	-0.07	-0.05	-0.03	-0.05	0.03
(45)	State innovativeness	-0.06	-0.06	0.05	0.06	0.09	**0.15**	0.05	0.09	-0.01	**0.14**	0.07	-0.07	-0.06	-0.01	0.01	-0.04	0.02	0.02	-0.05	**0.24**	**0.16**	0.04	-0.04
(46)	Firm age	-0.02	**-0.15**	**-0.20**	**0.48**	**0.48**	**0.13**	0.06	0.03	-0.07	**0.24**	**0.36**	**-0.42**	**-0.15**	-0.10	**0.62**	**0.20**	**0.19**	**0.36**	**0.32**	**0.13**	-0.07	-0.10	-0.05
(47)	Year dummies	-0.09	-0.09	**-0.12**	**-0.11**	**-0.15**	**-0.18**	0.10	**-0.16**	0.04	0.04	0.00	0.08	0.02	0.03	0.00	0.02	0.04	-0.02	0.03	**-0.13**	-0.09	-0.01	0.03

Table 6-20: Correlation matrix (continued)

		(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)	(41)	(42)	(43)	(44)	(45)	(46)	(47)
(24)	Manager's PhD	1.00																							
(25)	PI's PhD	**0.24**	1.00																						
(26)	Manager professor	**0.38**	0.10	1.00																					
(27)	PI professor	0.05	0.09	**0.36**	1.00																				
(28)	Manager's patents	**0.34**	0.09	**0.18**	-0.05	1.00																			
(29)	PI's patents	0.02	0.10	-0.08	0.09	**0.36**	1.00																		
(30)	Manager's public.	**0.60**	**0.14**	**0.51**	0.09	**0.53**	0.03	1.00																	
(31)	PI's public.	**0.11**	**0.24**	**0.20**	**0.39**	**0.12**	**0.37**	**0.26**	1.00																
(32)	Abstract readabil.	0.06	-0.02	-0.01	0.01	0.03	-0.05	0.00	0.02	1.00															
(33)	Project duration	0.01	0.08	-0.03	-0.03	-0.04	0.07	0.02	0.04	-0.03	1.00														
(34)	Invention activity	**-0.12**	**0.12**	**-0.15**	-0.10	0.09	**0.32**	-0.02	**0.14**	-0.09	0.02	1.00													
(35)	R&D capability	-0.01	0.06	-0.05	-0.05	-0.05	0.09	-0.04	-0.01	-0.05	-0.06	**0.33**	1.00												
(36)	Managerial capab.	**-0.21**	0.10	**-0.16**	0.00	-0.07	**0.27**	**-0.20**	0.08	-0.08	0.03	**0.65**	**0.22**	1.00											
(37)	Intellectual capab.	0.07	**0.23**	0.10	**0.13**	-0.07	-0.01	**0.17**	**0.29**	-0.08	0.09	0.09	0.03	0.05	1.00										
(38)	Project scope	0.04	-0.08	0.02	-0.05	-0.02	-0.10	0.05	**-0.13**	0.03	-0.10	-0.01	0.02	-0.02	-0.04	1.00									
(39)	Project category	**0.12**	**0.14**	-0.02	-0.09	0.07	0.05	0.06	0.00	0.06	**0.11**	0.07	0.07	0.10	-0.02	0.00	1.00								
(40)	Non-woman	0.06	**0.11**	0.03	-0.07	**0.15**	**0.12**	0.09	0.04	-0.10	**0.11**	**0.11**	**0.12**	**0.13**	**-0.11**	-0.05	0.08	1.00							
(41)	Non-minority	0.00	-0.05	-0.09	-0.10	-0.03	-0.01	0.00	-0.02	-0.03	0.00	**0.12**	-0.02	0.10	-0.01	0.07	0.07	**0.18**	1.00						
(42)	Non-HubZone	-0.02	0.03	-0.06	-0.02	0.00	-0.01	-0.06	0.05	0.06	**0.13**	0.08	0.03	0.01	0.04	0.05	0.08	-0.01	-0.04	1.00					
(43)	Ind. volatil. (2014)	0.02	**0.16**	-0.07	-0.05	0.02	0.02	0.00	0.04	-0.01	0.09	0.06	0.09	0.15	0.02	-0.10	**0.18**	**0.14**	0.00	0.07	1.00				
(44)	Ind. volatil. (t)	0.04	0.03	0.08	0.02	-0.07	-0.11	0.02	0.07	0.04	**-0.18**	-0.03	0.00	-0.03	-0.03	0.04	0.07	-0.09	0.00	0.07	0.07	1.00			
(45)	State innovativ.	-0.09	0.08	**-0.18**	**-0.12**	0.09	0.10	-0.03	0.04	-0.02	0.00	**0.17**	-0.01	**0.11**	-0.09	0.03	-0.05	**0.21**	0.01	0.02	**0.15**	-0.02	1.00		
(46)	Firm age	**-0.13**	0.00	-0.05	0.00	0.03	0.10	0.01	0.01	-0.05	0.06	**0.26**	**-0.11**	**0.34**	-0.07	0.05	**-0.11**	0.01	0.00	0.05	-0.05	-0.05	0.04	1.00	
(47)	Year dummies	0.05	-0.02	0.08	-0.03	0.06	-0.03	0.07	0.03	0.07	**-0.23**	-0.07	-0.08	-0.05	**-0.21**	0.01	0.03	-0.02	0.03	0.03	-0.01	**0.70**	-0.04	-0.02	1.00

Bold values indicate significant correlations (2-tailed)

Significance levels (0.11≤r<0.14 at p<0.05, 0.14≤r at p<0.01)

Chapter 7 - Results & Discussion (I): Testing Hypotheses of the Real Options Reasoning Model

7.1 Introduction

This chapter reports results of Part I analysis produced using SUR (GLS) procedure in STATA. Simultaneous equations were modelled using standardised data. The Breusch-Pagan test of independence of residuals was performed to test the null hypothesis of no contemporaneous correlation. The results of the Breusch-Pagan test for all systems of equations were statistically significant at $p<0.001$, indicating that the residuals are not independent, so the null hypothesis that correlation is zero could not be rejected. Given the presence of correlated error terms, it was confirmed that gains can be realised from the SUR procedure as it will produce more robust estimations (Kennedy 2003).

Under SUR GLS, R-squared is not a well-defined concept (Greene 2012). However, it can be used for descriptive purposes to get an insight into what percentage of variance in the dependent variables is explained by the predictors. R^2 for individual equations ranged from 0.13 to 0.41, while adjusted R^2 lied between 0.01 and 0.33, which indicates that the proportion of variance explained by individual variables was higher in some equations than in others.

The following sections present the results of hypotheses testing, and their validity is also discussed in light of robustness checks and sensitivity analyses. Then, the findings are interpreted and the main insights summarised.

7.2 Hypotheses Testing

Table 7-1 reports estimated coefficients and t-values for the full sample main regression model of Part I analysis, Table 7-2 for the cluster with no prior awards and Table 7-3 for the cluster with prior awards. The results are interpreted in relation to individual hypotheses subsequently.

Besides the focal hypothesised predictors, firm age is a significant control factor for firms from both clusters and is significantly and positively associated with firm performance. For firms with no prior awards, firm age also positively affects sales and employment yield, which demonstrates that established first-time award holders represent candidates for higher yield on investment to funders.

The findings imply that the real options investments have a limited ability in explaining innovation yield and performance, as demonstrated by low R^2 of corresponding equations, indicating that allocation of external funding per se does not improve innovation outcomes. However, innovative credentials of the state the firm is located in overall tend to have a positive and significant impact on innovation performance. This is in line with existing evidence that cluster membership, network ties and geographic proximity to innovation resources and R&D partners, can have a positive effect on innovation (e.g. Almeida and Kogut 1997; Almeida and Kogut 1999; Deeds et al. 1999). Additionally, innovation performance tends to spur in non-minority-owned firms, suggesting that socially and economically disadvantaged businesses may have a lack of resources necessary to advance R&D activities.

Table 7-1: System of equations (SUR) results – full sample

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level constructs												
Initial commitment	-0.19	-3.62***	-0.24	-4.51***	-0.06	-1.23	0.08	1.67	0.05	1.11	0.05	0.91
Discontinuation	-0.06	-0.52	-0.06	-0.51	-0.16	-1.40	0.02	0.16	-0.03	-0.29	-0.20	-1.86*
Fit	-0.11	-0.93	-0.13	-1.22	-0.02	-0.18	-0.08	-0.75	-0.09	-0.91	-0.02	-0.18
Portfolio-level constructs												
Fit	0.28	2.40**	0.31	2.81***	0.14	1.27	-0.03	-0.31	-0.01	-0.08	0.12	1.11
Control variables:												
Non-woman-owned	0.45	1.51	0.46	1.93	0.20	0.99	0.27	1.08	0.40	1.75*	0.25	1.27
Non-minority-owned	-0.11	-0.28	-0.23	-0.71	0.38	1.33	0.06	0.17	0.01	0.02	0.57	2.03**
Non-HubZone-owned	-0.41	-1.60	-0.52	-2.02**	-0.18	-0.75	-0.05	-0.20	-0.11	-0.44	0.12	0.48
Industry volatility	-0.21	-2.66***	-0.12	-1.61	0.03	0.36	-0.04	-0.55	0.05	0.73	0.06	0.90
State innovativeness	-0.05	-0.96	-0.06	-1.12	0.04	0.79	0.02	0.49	0.03	0.69	0.12	2.36**
Firm age	0.02	0.32	-0.11	-2.04**	-0.18	-3.34***	0.46	9.60***	0.47	9.63***	0.13	2.56**
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.12		0.15		0.09		0.26		0.29		0.12	
Adjusted R^2	0.08		0.12		0.05		0.23		0.26		0.08	

N= 367

*** p<0.01; ** p<0.05; * p<0.1

Table 7-2: System of equations (SUR) results – cluster with no prior awards

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level constructs												
Initial commitment	-0.43	-3.75***	-0.41	-4.76***	-0.09	-0.61	-0.14	-1.86*	-0.19	-2.31**	0.01	0.10
Discontinuation	-0.35	-1.68*	-0.27	-1.74*	-0.50	-1.88*	-0.18	-1.36	-0.25	-1.67	-0.26	-1.68*
Fit	0.21	1.10	0.22	1.55	0.13	0.51	0.12	0.95	0.20	1.42	0.05	0.34
Control variables:												
Non-woman-owned	0.46	0.95	0.68	2.23**	0.00	0.00	0.17	0.49	0.59	2.01**	-0.07	-0.21
Non-minority-owned	-0.08	-0.11	-0.24	-0.52	0.80	1.15	0.09	0.21	-0.01	-0.03	0.55	1.34
Non-HubZone-owned	-0.11	-0.28	-0.20	-0.69	-0.26	-0.58	-0.10	-0.36	-0.26	-0.88	-0.12	-0.46
Industry volatility	-0.21	-1.26	-0.06	-0.49	0.10	0.71	-0.12	-1.17	-0.01	-0.08	0.09	0.99
State innovativeness	0.03	0.26	0.02	0.25	0.08	0.67	0.02	0.30	0.01	0.19	0.05	0.78
Firm age	0.49	4.30***	0.37	4.30***	-0.06	-0.49	0.30	4.32***	0.36	4.20***	-0.01	-0.10
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.37		0.41		0.13		0.37		0.33		0.19	
Adjusted R^2	0.28		0.33		0.01		0.28		0.24		0.08	

N= 128

*** p<0.01; ** p<0.05; * p<0.1

Table 7-3: System of equations (SUR) results – cluster with prior awards

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level constructs												
Initial commitment	-0.03	-0.69	-0.08	-1.66	-0.02	-0.37	0.15	2.46**	0.13	2.22**	0.05	0.79
Discontinuation	0.07	0.65	0.03	0.28	-0.02	-0.21	0.06	0.39	0.00	0.03	-0.21	-1.43
Fit	-0.02	-0.16	-0.07	-0.66	0.01	0.11	-0.18	-1.39	-0.23	-1.85*	-0.04	-0.31
Portfolio-level constructs												
Initial commitment	-0.13	-2.19**	-0.15	-2.40**	-0.11	-2.01**	-0.09	-1.06	-0.05	-0.65	-0.06	-0.70
Sequencing	-0.19	-3.96***	-0.24	-4.95***	-0.15	-3.21***	-0.01	-0.20	-0.01	-0.13	-0.03	-0.46
Fit	0.17	1.74*	0.15	1.43	0.14	1.46	-0.11	-0.82	-0.14	-1.09	0.16	1.09
Control variables:												
Non-woman-owned	0.10	0.37	0.02	0.08	0.23	1.39	0.36	1.16	0.35	1.25	0.46	1.81*
Non-minority-owned	0.01	0.03	-0.11	-0.37	0.34	1.39	0.12	0.29	0.05	0.13	0.69	1.89*
Non-HubZone-owned	-0.24	-0.95	-0.39	-1.40	0.10	0.40	-0.10	-0.28	-0.11	-0.31	0.28	0.75
Industry volatility	-0.07	-0.69	0.01	0.08	-0.01	-0.12	-0.04	-0.30	0.05	0.43	-0.03	-0.28
State innovativeness	0.00	0.03	0.01	0.14	0.04	0.90	0.01	0.19	0.03	0.51	0.13	1.81*
Firm age	0.08	1.31	0.04	0.69	-0.09	-1.46	0.52	6.23***	0.50	6.29***	0.16	1.89*
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.16		0.18		0.13		0.25		0.27		0.13	
Adjusted R^2	0.10		0.12		0.06		0.20		0.22		0.06	

N= 239

*** p<0.01; ** p<0.05; * p<0.1

Resource Allocation to an Individual Option

H1-1: The magnitude of initial funding commitment has a negative effect on investment yield—(a) sales yield, (b) employment yield, (c) innovation yield, and firm performance—(d) sales performance, (e) employment performance, (f) innovation performance.

Testing Hypothesis 1-1 demonstrates overall support for the predicted relationship between initial funding commitment and performance, although variation exists between different samples and for different types of performance. The results from the full sample show a strong negative effect of the magnitude of initial funding on (a) sales yield ($\beta = -0.19$, $t = -3.62$) and (b) employment yield ($\beta = -0.24$, $t = -4.51$), but not for other types of performance. For firms with no prior awards, the effect of the magnitude of initial commitment is negative and significant at $p<0.05$ on (a) sales yield ($\beta = -0.43$, $t = -3.75$), (b) employment yield ($\beta = -0.41$, $t = -4.76$) and (e) employment performance ($\beta = -0.19$, $t = -2.31$); and at $p<0.1$ on (d) sales performance ($\beta = -0.14$, $t = -1.86$), but is insignificant on (c) innovation yield and (f) innovation performance. For firms with prior awards, contrary to expectations, the effect of the magnitude of initial commitment is *positive* and significant at $p<0.05$ on (d) sales performance ($\beta = 0.15$, $t = 2.46$) and (e) employment performance ($\beta = 0.13$, $t = 2.22$), but no effect is observed on other types of performance, which is mostly in accord with Hypothesis 1-6, discussed in more detail later in the chapter.

The interpretation of the findings is threefold. First, the results confirm that high initial commitment diminishes sales and employment performance of firms with no prior awards from both investment and corporate point of view. Firms with no prior awards are associated with higher risks because their profiles as borrowers are uncertain. Therefore, allocation of higher initial commitment to a new enterprise which has questionable chances of success, involves higher potential losses, increasing overall downside risks. Also, the propensity of investors to allocate larger initial grants to certain projects signifies their higher stake in those projects, which may be driven by investors' opportunism. As a result, the tendency to magnify initial commitment offsets the potential flexibility benefits. When sunk costs are high, it is more difficult to discontinue failing projects, increasing the chances of potential escalation of commitment (Adner and Levinthal 2004b). Taken together, higher potential loss-making, opportunistic behaviour and escalation of commitment, put higher pressure on the overall government venture capital budget, which can result in allocation of even smaller or no grants to other potentially promising projects, minimising potential upward gain offered by ROR logic, which allows to explore multiple opportunities concurrently at a low cost.

At the corporate level, higher allocation of initial capital decreases firms' productivity and efficiency, so firms can achieve more with fewer resources through incremental learning and experimentation. The reason behind such phenomenon may be explained by a variety of underlying business start-up motives, which are not always linked to economic rationality, so entrepreneurial behaviour may be non-utility-maximisation driven (Scheingberg and MacMillan 1988; Birley and Westhead 1994), in which case fewer resources can yield better results (Burke et al. 2000). Second, contrary to the hypothesis, the effect of the magnitude of initial commitment has a positive effect on sales and employment performance of firms with prior awards. Although extra cash from individual project awards might advantage continuing participants of the programme, such awards have no effect on the overall yield for investors, jeopardising the rationale for funding. Finally, the magnitude of initial commitment has no effect on innovation outcomes, implying that the size of the financial award is unrelated to inventive capacity. This finding is consistent with the evidence from the study by Klingebiel and Adner (2015), which also found no association between low initial commitment and innovation performance.

H1-2: Funding discontinuation has a negative effect on investment yield—(a) sales yield, (b) employment yield, (c) innovation yield, and firm performance—(d) sales performance, (e) employment performance, (f) innovation performance.

Testing Hypothesis 1-2 on the full sample and the sample with prior awards shows no support for the predicted relationship between discontinuation and performance. However, the effect of discontinuation on performance of firms with no prior awards is negative yet weak on (a) sales yield (β = -0.35, t = 1.68), (b) employment yield (β = -0.27, t = -1.74), (c) innovation yield (β = -0.50, t = -1.88) and (f) innovation performance (β = -0.26, t = -1.68). Hence, overall Hypothesis 1-2 is partially supported.

It was noted that discontinuation can potentially add value to the investment process only if there are other options in the portfolio (Klingebiel and Adner 2015). As such, the results demonstrate that first-time award holders tend to suffer more from the decision to discontinue funding in comparison to their established counterparts because they have no other options to explore in the portfolio. Another thought-provoking insight is related to the finding that unlike the magnitude of initial commitment, discontinuation has a negative effect on innovation performance. As was stated in the previous chapter, R&D process calls for extended funding to enable capability building (Kogut and Kulatilaka 1994b), so untimely seizure of funding will interrupt the process of learning and experimentation necessary for the advancement of innovation activity (Trigeorgis 1996).

H1-3: Fit of funding decisions, i.e. low initial funding commitment and discontinuation or high initial commitment and continuation, has a positive effect on investment yield—*(a) sales yield, (b) employment yield, (c) innovation yield, and firm performance*—*(d) sales performance, (e) employment performance, (f) innovation performance.*

No support was found for Hypothesis 1-3. The proposed benefits of matching resource allocation decisions in a way that corresponds to the prescribed ROR logic were not observed at the individual option level in neither full nor split samples.

Resource Allocation to a Portfolio of Options

H1-4: The performance effect of fit of funding decisions is greater at the at the cumulated portfolio level than at the individual option level.

Although the effect of fit of funding decisions is not visible for individual options and split samples, fit has a strong positive effect on (a) sales yield ($\beta = 0.28$, $t = 2.40$) and (b) employment yield ($\beta = 0.31$, $t = 2.81$) at the portfolio level for a full sample, which indicates the importance of consistency and correspondence of decisions at the macro level on investment outcomes. Hence, Hypothesis 1-4 is mostly supported.

The finding offers a critical insight for the theory of investment under ROR. Despite the lack of apparent gains associated with matching funding allocation decisions at the individual option level, significant benefits can be realised when matching is practised consistently and in relation to the entire portfolio. Recall from the preceding chapter that SBIR government venture capital implicitly applies ROR logic of fitting funding allocation decisions in relation to half of projects in the sample. The results demonstrate that matching resource allocation decisions in a manner that distinguishes ROR from sequential decision-making has a strong impact on return on investment from commercialisation and employment creation activities. In other words, when fit is achieved by aligning low initial commitment and discontinuation, it enhances the propensity to abandon unpromising low-stake projects. On the other hand, when fit is achieved by aligning high initial commitment and continuation, it indicates that when projects are associated with higher future potential from the outset, moving them through the stages increases chances of realising investment benefits from promising high-stake projects.

The finding conflicts with the result reported by Klingebiel and Adner (2015), who found a significant and positive effect of fit on innovation performance. In contrast, the present study found no impact of fit on innovation outcomes, but on sales and employment yield. The disparity might be contextual. In the case of government venture funding, the underlying intuition is that ROR logic, although might enhance corporate benefits, is essentially an investment tool, which, when exercised properly, promises higher returns to budget holders.

H1-5: For firms with prior awards, high rate of funding sequencing has a negative effect on investment yield–(a) sales yield, (b) employment yield, (c) innovation yield, and firm performance–(d) sales performance, (e) employment performance, (f) innovation performance.

The results show strong support for Hypothesis 1-5. Higher propensity to sequence has a significant negative effect on investment outcomes, namely, (a) sales yield (β = -0.19, t= -3.96), (b) employment yield (β = -0.24, t = -4.95) and (c) innovation yield (β = -0.15, t = -3.21), but not on firm-level outcomes.

The findings demonstrate that inconsistent application of the ROR logic, whereby too many projects are sequenced from early to late stages, erodes strategic value offered by option-like investments. The logic dictates that unpromising projects should be discarded early on, and only the most promising projects should be selected for subsequent funding stages. Hence, increased propensity to sequence is a direct result of an inability to discontinue failing projects, which undermines the successful execution of decision-making under the ROR approach.

H1-6: An opening of a new individual project has a positive effect on investment yield–(a) sales yield, (b) employment yield, (c) innovation yield, and firm performance–(d) sales performance, (e) employment performance, (f) innovation performance of firms with no prior awards, but an addition of a new individual project to the portfolio of firms with prior awards has no effect.

In the presence of existing portfolio configurations, there were no effects from additional individual options on investment yield, indicating that new options are subadditive, supporting Hypothesis 1-6. In addition to the strong negative effect of sequencing (H1-5), the magnitude of initial commitment at the cumulated portfolio level has a significant and negative effect on (a) sales yield (β = -0.13, t = -2.19), (b) employment yield (β = -0.15, t = -2.40) and (c) innovation yield (β = -0.11, t = -2.01), further corroborating Hypothesis 1-1.

The following results show that there is a delusion effect of perceived benefits of additional funding: while established awardees manage to convert extra cash from additional projects into increasing sales and number of employees, possibly by engaging into marketing and hiring activities, there are no gains from the investment point of view. Financing of more projects does not increase the value of the portfolio, indicating that additional individual options are non-additive.

7.3 Robustness Checks

Alternative Operationalisations of Real Options Reasoning Constructs

As was discussed in the research methodology chapter, ROR constructs can be operationalised either on the continuous or binary scale. Because continuous scale offers richer data to gain insights into the phenomenon, it was decided to be more suitable for the main analysis. However, alternative binary operationalisation can be used for robustness checks. To check the robustness of the primary findings, the base model was estimated using the second operationalisation of ROR constructs; namely, initial commitment at both project and portfolio levels, and sequencing. For both variables, low values were coded as a base category of 1.

Results of SUR estimation with the alternative operationalisation of ROR constructs are reported in Table 7-4 for the full sample, in Table 7-5 for the cluster with no prior awards and in Table 7-6 for the cluster with prior awards.

Effect of all predictors included in the full sample model remained unchanged. In the sample of firms with no prior awards, effects of two focal relationships have changed. First, initial commitment for sales and employment performance became insignificant. Second, discontinuation became insignificant for sales yield and employment yield, but is significant at $p<0.1$ for innovation outcomes. These findings further confirm that a) the effect of ROR elements is strongest on investment yield and b) the effect of discontinuation, although weak, is most profound on innovation outcomes. They add to the conclusion that in the absence of other alternatives in the portfolio, premature termination of R&D projects is likely to have detrimental effects on innovation activity of firms.

In the sample of firms with prior awards, low initial commitment of an individual option has a positive effect on sales and employment yield, but not on sales and employment performance, which is the opposite in the base model. This indicates that individual options are additive to the portfolio *only* if initial commitment is low. Next, in contrast to the base model, low initial commitment and low sequencing at the portfolio level individually have no direct effect on innovation yield, but have a significant and positive effect when matched. Overall, fit is positive and significant for all yield measures.

Although some differences exist between the base model and the model with alternative operationalisations, essentially, the results of both models agree that initial commitment and sequencing have a positive impact on investment yield when low, or when matched. Additionally, discontinuation has a negative, though weak effect on innovation outcomes, when firms have no other R&D options in the pipeline.

Table 7-4: Robustness check – system of equations (SUR) results – alternative operationalisation of ROR constructs – full sample

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level constructs												
Initial commitment (dummy)	0.36	3.29***	0.44	4.08***	0.07	0.64	-0.12	-1.19	-0.09	-0.90	-0.11	-1.06
Discontinuation	-0.05	-0.44	-0.04	-0.40	-0.15	-1.38	0.01	0.13	-0.03	-0.31	-0.21	-1.89*
Fit	-0.10	-0.84	-0.12	-1.10	-0.01	-0.12	-0.08	-0.80	-0.09	-0.95	-0.02	-0.19
Portfolio-level constructs												
Fit	0.25	2.13**	0.27	2.44**	0.13	1.13	-0.02	-0.15	0.00	0.02	0.13	1.18
Control variables:												
Non-woman-owned	0.48	1.60	0.49	2.07**	0.20	1.00	0.27	1.05	0.39	1.72	0.24	1.22
Non-minority-owned	-0.08	-0.21	-0.20	-0.61	0.38	1.33	0.05	0.15	0.00	0.00	0.56	1.99**
Non-HubZone-owned	-0.36	-1.41	-0.46	-1.79*	-0.17	-0.68	-0.07	-0.29	-0.12	-0.50	0.11	0.44
Industry volatility	-0.22	-2.85***	-0.14	-1.85*	0.02	0.25	-0.03	-0.43	0.05	0.81	0.06	0.93
State innovativeness	-0.05	-0.89	-0.05	-1.03	0.04	0.79	0.02	0.46	0.03	0.67	0.12	2.33**
Firm age	0.01	0.23	-0.11	-2.17**	-0.18	-3.41***	0.46	9.69***	0.47	9.71***	0.13	2.57**
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.12		0.15		0.09		0.26		0.29		0.12	
Adjusted R^2	0.08		0.11		0.05		0.23		0.26		0.08	

N= 367

*** p<0.01; ** p<0.05; * p<0.1

Table 7-5: Robustness check – system of equations (SUR) results – alternative operationalisation of ROR constructs – cluster with no prior awards

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level constructs												
Initial commitment (dummy)	0.44	3.49***	0.48	3.53***	-0.08	-0.32	-0.06	-1.61	0.16	1.37	-0.15	-0.98
Discontinuation	-0.29	-1.35	-0.21	-1.31	-0.49	-1.85*	-0.17	-1.30	-0.23	-1.49	-0.27	-1.73*
Fit	0.15	0.79	0.17	1.17	0.10	0.42	0.10	0.83	0.17	1.21	0.04	0.29
Control variables:												
Non-woman-owned	0.45	0.92	0.66	2.10**	0.01	0.01	0.17	0.50	0.59	1.98**	-0.06	-0.19
Non-minority-owned	-0.08	-0.11	-0.21	-0.45	0.75	1.07	0.07	0.16	-0.02	-0.05	0.51	1.24
Non-HubZone-owned	-0.01	-0.03	-0.11	-0.37	-0.24	-0.54	-0.08	-0.29	-0.21	-0.73	-0.12	-0.46
Industry volatility	-0.21	-1.25	-0.06	-0.50	0.11	0.72	-0.12	-1.17	-0.01	-0.08	0.09	1.01
State innovativeness	0.02	0.18	0.01	0.13	0.08	0.67	0.02	0.29	0.01	0.14	0.05	0.80
Firm age	0.50	4.18***	0.37	4.21***	-0.07	-0.53	0.30	4.29***	0.36	4.16***	-0.01	-0.16
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.32		0.36		0.13		0.28		0.31		0.19	
Adjusted R^2	0.23		0.27		0.01		0.18		0.22		0.08	

N= 128

*** p<0.01; ** p<0.05; * p<0.1

Table 7-6: Robustness check – system of equations (SUR) results – alternative operationalisation of ROR constructs – cluster with prior awards

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level constructs												
Initial commitment (dummy)	0.16	1.73*	0.22	2.19**	0.10	1.01	-0.22	-1.63	-0.20	-1.62	-0.03	-0.21
Discontinuation	0.07	0.68	0.04	0.33	-0.01	-0.13	0.03	0.18	-0.02	-0.16	-0.21	-1.47
Fit	-0.01	-0.07	-0.05	-0.53	0.02	0.27	-0.18	-1.37	-0.23	-1.87*	-0.03	-0.24
Portfolio-level constructs												
Initial commitment (dummy)	0.21	1.75*	0.28	2.27**	0.11	1.00	0.20	1.21	0.16	1.09	-0.06	-0.35
Sequencing (dummy)	0.25	2.35**	0.31	2.76***	0.17	1.65	0.17	1.20	0.15	1.12	0.09	0.62
Fit	0.26	2.56**	0.27	2.46**	0.20	2.07**	-0.05	-0.36	-0.09	-0.68	0.15	1.05
Control variables:												
Non-woman-owned	0.12	0.41	0.04	0.17	0.23	1.34	0.34	1.09	0.34	1.21	0.43	1.68*
Non-minority-owned	-0.01	-0.03	-0.13	-0.41	0.31	1.24	0.12	0.29	0.06	0.14	0.67	1.83*
Non-HubZone-owned	-0.31	-1.22	-0.45	-1.60	0.04	0.14	-0.18	-0.53	-0.17	-0.50	0.21	0.57
Industry volatility	-0.05	-0.53	0.02	0.20	0.00	-0.06	-0.01	-0.09	0.07	0.63	-0.03	-0.27
State innovativeness	-0.01	-0.23	-0.01	-0.10	0.03	0.56	0.01	0.15	0.03	0.52	0.12	1.61
Firm age	0.06	1.07	0.02	0.29	-0.09	-1.49	0.52	6.27***	0.49	6.28***	0.18	2.11**
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.14		0.15		0.10		0.24		0.27		0.12	
Adjusted R^2	0.07		0.08		0.03		0.19		0.22		0.06	

N= 239
*** p<0.01; ** p<0.05; * p<0.1

Robust Standard Errors

The tests reported in the previous chapter indicated that the data might suffer from heteroscedasticity. To control for possible effects of this problem, it is necessary to estimate robust standard errors which produce unbiased p-values in cases when residual terms are unequally distributed. Hence, to avoid any potential misinterpretation of hypotheses tests, Seemingly Unrelated Estimation (SUEST) procedure was carried out in STATA for each regression model. Like SUR, SUEST produces estimations for a series of simultaneous equations and then combines parameter estimates with associated variance matrices to return robust standard errors (StataCorp 2013).

Results of SUEST estimation are reported in Appendix 22 for the full sample, in Appendix 23 for the cluster with no prior awards and in Appendix 24 for the cluster with prior awards. As Allison (1999) pointed out, the use of robust standard errors does not change coefficient estimates but produces more accurate p-values. As a result, coefficient estimates produced under SUEST are identical to the ones produced under SUR, but t-values and corresponding p-values have changed to reflect robust standard errors.

Estimates of t-values of the full and split sample models have only changed slightly under SUEST, and respective variables retained statistically significant effects on tested dependent variables. Therefore, it can be concluded that the interpretation of hypotheses remains unchanged even when robust standard errors are used.

7.4 Sensitivity Analyses

Recall from the research methodology chapter that the measures of sales and employment yield might suffer from overstatement bias because they do not reflect the change over the period from *t* to t_{2014}, but instead, refer to the closing period. This means that the measures of sales and employment yield included in the base SUR model represent 100% growth, which may inflate parameter estimates. To address this problem, sensitivity analyses were conducted using a more realistic 10% growth rate of sales and employment since year *t*.

Appendix 25 shows how estimates change when sales and employment yield is reduced from 100% growth to 10% growth. Since other dependent variables in the model were unaffected by potential overestimation bias, only two equations from respective samples are presented in Appendix 25. In the full sample, all main effects remained unchanged, except two controls in the employment yield equation became statistically insignificant. In the sample with no prior awards, the effect of discontinuation on sales and employment yield changed from significant at $p<0.10$ to insignificant. In the sample with prior awards, the effect of portfolio level fit has a weak positive significant effect on employment yield in comparison to no effect under the base model. Additionally, Appendix 26 presents t-values based on robust standard errors for equations with adjusted sales and employment yield as dependent variables. None of the hypothesised relationships significantly changed their effects. In fact, in the sample with prior awards, the effect of portfolio level fit has a significant positive effect at $p<0.05$ on employment yield which has not been revealed under the base model. The latter suggests that the chosen primary estimation method of SUR produces the most conservative estimation parameters.

Overall, the differences in estimates produced by the base model and the adjusted model are minute, which signifies that the findings are not sensitive to potential variations in the dependent variables, so hypotheses testing holds true.

7.5 Summary

Table 7-7 presents a summary of findings from the base SUR model in relation to hypotheses tested in Part I analysis. Literature investigating effects of distinct ROR elements on performance is sparse. For example, a recent study by Klingebiel and Adner (2015) tested the effect of low initial commitment, discontinuation, sequencing and fit on innovation performance. The authors found a strong positive impact of sequencing and fit on innovation performance. However, low initial commitment and discontinuation showed no direct effect on performance, so it was concluded that these elements have no direct relationship with performance in general.

The results presented in this section extend the empirical inquiry into the relationship between the distinct elements mandated by the ROR logic and performance. First, the study found that the magnitude of initial commitment and high rate of sequencing have a diminishing effect on investment yield. The value from the investment process can be extracted when positioning trial commitments are small, and follow-up funds are allocated to selected projects only. That is, discontinuation decision has to be exercised in a disciplined manner. Second, discontinuation has a negative, yet weak effect on investment yield and innovation performance, when there are no other options in the portfolio, such as in the case of first-time award holders. Accounting for the fact that development of R&D options involves extensive learning, firms with no prior awards should have a priority for follow-on funding to maximise the chances of successful innovation and commercialisation. Third, fit of funding decisions has a significant and positive effect on investment yield exclusively at the cumulated portfolio level, indicating that long-term investment gains from matching funding allocation decisions under the ROR approach can only be realised when implemented consistently and across the entire portfolio of options. Finally, the study found evidence that the overall portfolio is subadditive with regard to the value of individual options. For firms that previously received funding, the effect of opening new options on performance is cancelled in the presence of existing options in the portfolio, unless the initial commitment to the additional option is small, as demonstrated by robustness checks. Overall, the results show a strong effect of ROR elements on investment outcomes, but very limited effect on firm-level outcomes. At its core, real options logic is a strategic investment tool which benefits decision-makers. In the present empirical context, the effect of explicitly following ROR logic is more pronounced in relation to investors because they are decision-makers.

In sum, the findings presented here simultaneously validate a direct positive impact of real options logic and delineate its boundary conditions in the context of government venture funding. The analysis confirms that distinct ROR constructs have differential effects on (i) different types of performance, i.e. sales, employment versus innovation; (ii) investors versus firms, (iii) whether the firm had other options in the portfolio or not. The results of hypotheses are consistent with estimations based on robust standard errors and not sensitive to a potential overstatement of dependent variables. It can be concluded that the overall positive effects of allocated funding on investment yield tend to decrease the more money or, the more grants the firms receive.

Table 7-7: Summary of Part I hypotheses testing results

Hypothesis	Hypothesised relationship	Level	Full Sample			Firm Cluster: No prior awards			Firm Cluster: With prior awards		
			β	t-value	Result	β	t-value	Result	β	t-value	Result
H1-1a	Initial commitment -> Sales Yield	Project	**-0.19**	**-3.62*** **	**S**	**-0.43**	**-3.75*** **	**S**	-0.03	-0.69	NS
H1-1b	Initial commitment -> Employment Yield	Project	**-0.24**	**-4.51*** **	**S**	**-0.41**	**-4.76*** **	**S**	-0.08	-1.66	NS
H1-1c	Initial commitment -> Innovation Yield	Project	-0.06	-1.23	NS	-0.09	-0.61	NS	-0.02	-0.37	NS
H1-1d	Initial commitment -> Sales Performance	Project	0.08	1.67	NS	-0.14	-1.86*	PS	0.15	2.46**	CF
H1-1e	Initial commitment -> Employment Performance	Project	0.05	1.11	NS	**-0.19**	**-2.31** **	**S**	0.13	2.22**	CF
H1-1f	Initial commitment -> Innovation Performance	Project	0.05	0.91	NS	0.01	0.10	NS	0.05	0.79	NS
H1-2a	Discontinuation -> Sales Yield	Project	-0.06	-0.52	NS	-0.35	-1.68*	PS	0.07	0.65	NS
H1-2b	Discontinuation -> Employment Yield	Project	-0.06	-0.51	NS	-0.27	-1.74*	PS	0.03	0.28	NS
H1-2c	Discontinuation -> Innovation Yield	Project	-0.16	-1.40	NS	-0.50	-1.88*	PS	-0.02	-0.21	NS
H1-2d	Discontinuation -> Sales Performance	Project	0.02	0.16	NS	-0.18	-1.36	NS	0.06	0.39	NS
H1-2e	Discontinuation -> Employment Performance	Project	-0.03	-0.29	NS	-0.25	-1.67	NS	0.00	0.03	NS
H1-2af	Discontinuation -> Innovation Performance	Project	-0.20	-1.86*	PS	-0.26	-1.68*	PS	-0.21	-1.43	NS
H1-3a	Fit -> Sales Yield	Project	-0.11	-0.93	NS	0.21	1.10	NS	-0.02	-0.16	NS
H1-3b	Fit-> Employment Yield	Project	-0.13	-1.22	NS	0.22	1.55	NS	-0.07	-0.66	NS
H1-3c	Fit -> Innovation Yield	Project	-0.02	-0.18	NS	0.13	0.51	NS	0.01	0.11	NS
H1-3d	Fit -> Sales Performance	Project	-0.08	-0.75	NS	0.12	0.95	NS	-0.18	-1.39	NS
H1-3e	Fit -> Employment Performance	Project	-0.09	-0.91	NS	0.20	1.42	NS	-0.23	-1.85*	CF
H1-3f	Fit -> Innovation Performance	Project	-0.02	-0.18	NS	0.05	0.34	NS	-0.04	-0.31	NS
H1-4a	Fit -> Sales Yield	Portfolio	**0.28**	**2.40** **	**S**	-	-	NA	0.17	1.74*	PS
H1-4b	Fit-> Employment Yield	Portfolio	**0.31**	**2.81*** **	**S**	-	-	NA	0.15	1.43	NS
H1-4c	Fit -> Innovation Yield	Portfolio	0.14	1.27	NS	-	-	NA	0.14	1.46	NS
H1-4d	Fit -> Sales Performance	Portfolio	-0.03	-0.31	NS	-	-	NA	-0.11	-0.82	NS
H1-4e	Fit -> Employment Performance	Portfolio	-0.01	-0.08	NS	-	-	NA	-0.14	-1.09	NS
H1-4f	Fit -> Innovation Performance	Portfolio	0.12	1.11	NS	-	-	NA	0.16	1.09	NS
H1-5a	Sequencing -> Sales Yield	Portfolio	-	-	NA	-	-	NA	**-0.19**	**-3.96*** **	**S**
H1-5b	Sequencing -> Employment Yield	Portfolio	-	-	NA	-	-	NA	**-0.24**	**-4.95*** **	**S**
H1-5c	Sequencing -> Innovation Yield	Portfolio	-	-	NA	-	-	NA	**-0.15**	**-3.21*** **	**S**
H1-5d	Sequencing -> Sales Performance	Portfolio	-	-	NA	-	-	NA	-0.01	-0.20	NS
H1-5e	Sequencing -> Employment Performance	Portfolio	-	-	NA	-	-	NA	-0.01	-0.13	NS
H1-5f	Sequencing -> Innovation Performance	Portfolio	-	-	NA	-	-	NA	-0.03	-0.46	NS
H1-6a	Initial commitment -> Sales Yield	Portfolio	-	-	NA	-	-	NA	**-0.13**	**-2.19** **	**S**
H1-6b	Initial commitment -> Employment Yield	Portfolio	-	-	NA	-	-	NA	**-0.15**	**-2.40** **	**S**
H1-6c	Initial commitment -> Innovation Yield	Portfolio	-	-	NA	-	-	NA	**-0.11**	**-2.01** **	**S**
H1-6d	Initial commitment -> Sales Performance	Portfolio	-	-	NA	-	-	NA	-0.09	-1.06	NS
H1-6e	Initial commitment -> Employment Performance	Portfolio	-	-	NA	-	-	NA	-0.05	-0.65	NS
H1-6f	Initial commitment -> Innovation Performance	Portfolio	-	-	NA	-	-	NA	-0.06	-0.70	NS

Notes: S – supported, NS – not supported, PS – partially supported, CF – contrary finding, NA – not applicable;
*** p<0.01; ** p<0.05; * p<0.1

Chapter 8 - Results & Discussion (II): Testing Hypotheses of the Signalling and Attention-Based View Models

8.1 Introduction

The focus of the present chapter is to convey the findings of Part II analysis obtained from OLS and Logit regression models in STATA using standardised data. Specifically, OLS model was used to test hypotheses related to the effects of signalling constructs on the magnitude of initial commitment, while Logit model was used to test hypotheses related to the effects of signalling constructs on the likelihood of subsequent funding discontinuation.

As in the previous results chapter, the analysis was conducted for the full sample as well as for the split samples comprising a cluster with no prior awards and a cluster with prior awards. R^2 for three OLS models were 0.20, 0.34 and 0.27 and adjusted R^2 were 0.10, 0.04 and 0.11, while Pseudo R^2 for Logit models were 0.22, 0.35 and 0.30, respectively. This indicates that individual variables explain up to a third of the variance in the dependent variables; however, when adjusted for the number of independent variables in the model, their contribution reduces by a third.

Subsequent sections discuss the results of hypotheses testing, and then present robustness checks to scrutinise the validity of findings. To sum up the chapter, conclusions are drawn from Part II analysis and the primary insights outlined.

8.2 Hypotheses Testing

Table 8-1 reports estimated coefficients and t-values for the full sample OLS regression model on initial commitment, Table 8-2 for the cluster with no prior awards and Table 8-3 for the cluster with prior awards. Moreover, Table 8-4 displays estimated coefficients and t-values for the full sample Logit regression model on discontinuation, Table 8-5 for the cluster with no prior awards and Table 8-6 for the cluster with prior awards. To test for the independent effects of each signal category, the variables measuring each construct were included separately in Models 1 through 4, concluding with the full model. Model 1 includes the variables representing more observable signals, i.e. TMT legitimacy and efficacy; Model 2 includes less observable signals, i.e. capabilities; Model 3 includes attention-distorting signals, i.e. project appeal characteristics and existing portfolio characteristics respectively; Model 4 is a full model which includes all categories of signals. The results are discussed in light of original hypotheses in the following sections.

Firm age is a significant control factor for a full sample of firms and is positively associated with the magnitude of initial funding commitment. This result is consistent with findings of prior studies that investors favour older firms because they are perceived as less risky (Sanders and Boivie 2004; Daily et al. 2005). On the other hand, state innovativeness is a significant controlling variable in the Logit model which increases the likelihood of discontinuation, particularly for firms with prior awards. It may be, that availability of geographic-specific innovation resources reduces the importance of government venture funding continuation as support can be received elsewhere in the state.

Overall, the findings imply that signalling constructs have a limited ability in explaining funding allocation decisions, as demonstrated by the small number of statistically significant independent variables, indicating that allocation of external funding may be driven by other factors which have not been captured by the model. In particular, firms with no prior awards remain a 'black box'.

Table 8-1: Ordinary leasts squares (OLS) model results – full sample – DV: initial commitment

	(1) Observables		(2) Unobservables		(3) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:								
Role legitimacy								
Manager CEO	-0.05	-0.35					-0.05	-0.38
PI CEO	-0.04	-0.30					-0.02	-0.12
PI's firm tenure	-0.21	-2.38**					-0.23	-2.62***
Manager's technical experience	-0.13	-1.30					-0.11	-1.18
PI's technical experience	0.15	1.98**					0.10	1.28
Manager's entrepreneurial experience	-0.17	-1.82*					-0.14	-1.48
PI's entrepreneurial experience							0.05	0.57
Resource legitimacy	0.04	0.44						
Manager's elite education	0.14	1.65					0.12	1.33
PI's elite education	-0.10	-1.35					-0.07	-0.84
Manager's MBA	-0.17	-0.88					-0.20	-1.11
PI's MBA	0.15	0.64					0.06	0.24
Manager's PhD	0.14	0.91					0.13	0.81
PI's PhD	0.06	0.19					-0.01	-0.04
Manager's professorship	0.10	0.62					0.12	0.70
PI's professorship	0.26	1.54					0.29	1.72
Intellectual legitimacy								
Manager's patents	-0.09	-1.00					-0.10	-1.05
PI's patents	0.16	2.36**					0.15	2.03**
Manager's publications	0.01	0.13					0.01	0.08
PI's publications	-0.18	-2.17**					-0.17	-2.01*
Abstract readability	0.25	0.25					0.06	0.06
Capabilities								
R&D capability			0.73	1.19			0.56	0.90
Managerial capability			0.42	1.43			-0.01	-0.02
Intellectual capability			-0.24	-0.63			-0.19	-0.40
Project appeal								
Project scope (broad)					-0.30	-2.81***	-0.29	-2.36**
Cancer detection and diagnosis research					0.22	1.30	0.24	1.33
Cancer treatment research					0.20	1.16	0.20	1.03
Cancer biology research					0.58	2.54**	0.56	2.37**
Control variables:								
Non-woman-owned	0.06	0.26	0.11	0.53	0.14	0.67	-0.01	-0.03
Non-minority-owned	0.15	0.49	0.14	0.46	0.16	0.55	0.16	0.55
Non-HubZone-owned	-0.13	-0.47	-0.27	-1.05	-0.29	-1.16	-0.12	-0.45
Industry volatility	-0.04	-0.27	0.05	0.42	-0.01	-0.11	-0.09	-0.69
State innovativeness	0.04	0.59	0.02	0.33	0.02	0.35	0.03	0.55
Firm age	0.20	2.60**	0.04	0.71	0.08	1.51	0.23	2.73***
Year dummies	Incl.		Incl.		Incl.		Incl.	
R^2	0.16		0.05		0.08		0.20	
Adjusted R^2	0.08		0.01		0.04		0.10	

N= 367

*** p<0.01; ** p<0.05; * p<0.1

Table 8-2: Ordinary least squares (OLS) model results – cluster with no prior awards – DV: initial commitment

	(1) Observables		(2) Unobservables		(3) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:								
Role legitimacy								
Manager CEO	-0.11	-0.56					-0.14	-0.67
PI CEO	0.18	0.91					0.24	1.16
PI's firm tenure	-0.35	-1.92*					-0.34	-1.83*
Manager's technical experience	-0.04	-0.28					-0.02	-0.17
PI's technical experience	0.03	0.28					0.00	0.03
Manager's entrepreneurial experience	-0.15	-1.19					-0.19	-1.29
PI's entrepreneurial experience	0.09	0.60					0.13	0.76
Resource legitimacy								
Manager's elite education	-0.04	-0.29					-0.07	-0.52
PI's elite education	-0.05	-0.52					-0.06	-0.56
Manager's MBA	-0.11	-0.48					-0.09	-0.34
PI's MBA	0.29	0.78					0.16	0.40
Manager's PhD	0.04	0.13					0.03	0.10
PI's PhD	0.27	0.80					0.33	0.81
Manager's professorship	-0.06	-0.25					-0.10	-0.37
PI's professorship	0.47	2.24**					0.51	2.16**
Intellectual legitimacy								
Manager's patents	-0.01	-0.05					0.01	0.03
PI's patents	0.08	0.76					0.09	0.75
Manager's publications	-0.15	-1.05					-0.22	-1.37
PI's publications	-0.13	-1.29					-0.11	-0.86
Abstract readability	0.04	0.03					-0.19	-0.12
Capabilities								
R&D capability			0.81	1.11			0.27	0.31
Managerial capability			-0.26	-0.57			-1.01	-1.74*
Intellectual capability			-0.57	-0.98			-0.15	-0.17
Project appeal								
Project scope (broad)					-0.19	-1.14	-0.10	-0.48
Cancer detection and diagnosis research					-0.10	-0.41	0.06	0.18
Cancer treatment research					-0.10	-0.38	0.15	0.47
Cancer biology research					0.25	0.69	0.21	0.51
Control variables:								
Non-woman-owned	0.06	0.37	-0.11	-0.31	-0.03	-0.09	0.15	0.37
Non-minority-owned	0.21	0.51	0.30	0.66	0.20	0.44	0.28	0.53
Non-HubZone-owned	0.03	0.33	-0.24	-0.81	-0.22	-0.74	-0.01	-0.04
Industry volatility	-0.08	0.17	-0.15	-0.92	-0.17	-1.04	-0.06	-0.33
State innovativeness	0.04	0.08	0.00	0.02	0.01	0.15	0.04	0.46
Firm age	0.19	0.12	0.02	0.26	0.03	0.39	0.25	1.88*
Year dummies	Incl.		Incl.		Incl.		Incl.	
R^2	0.30		0.11		0.10		0.34	
Adjusted R^2	0.06		-0.01		-0.03		0.04	

N= 128

*** p<0.01; ** p<0.05; * p<0.1

Table 8-3: Ordinary least squares (OLS) model results – cluster with prior awards – DV: initial commitment

	(1) Observables		(2) Unobservables		(3-1) Distortions		(3-2) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:										
Role legitimacy										
Manager CEO	-0.02	-0.10							-0.10	-0.47
PI CEO	-0.17	-0.85							-0.16	-0.79
PI's firm tenure	-0.16	-1.19							-0.16	-1.14
Manager's technical experience	-0.12	-0.88							-0.10	-0.77
PI's technical experience	0.20	1.75*							0.16	1.25
Manager's entrepreneurial experience	-0.21	-1.65							-0.15	-1.12
PI's entrepreneurial experience	0.03	0.21							0.05	0.42
Resource legitimacy										
Manager's elite education	0.18	1.62							0.16	1.43
PI's elite education	-0.10	-0.88							-0.04	-0.40
Manager's MBA	-0.17	-0.51							-0.19	-0.56
PI's MBA	-0.03	-0.09							-0.20	-0.53
Manager's PhD	0.22	0.97							0.14	0.58
PI's PhD	-0.16	-0.31							-0.29	-0.52
Manager's professorship	0.19	0.72							0.15	0.54
PI's professorship	0.12	0.52							0.16	0.72
Intellectual legitimacy										
Manager's patents	-0.14	-1.20							-0.19	-1.68
PI's patents	0.19	1.99**							0.17	1.76*
Manager's publications	0.06	0.45							0.11	0.79
PI's publications	-0.22	-1.86*							-0.23	-2.02**
Abstract readability	0.70	0.54							0.18	0.14
Capabilities										
R&D capability			0.61	0.67					-0.03	-0.03
Managerial capability			0.59	1.48					0.20	0.45
Intellectual capability			-0.19	-0.40					-0.19	-0.32
Project appeal										
Project scope (broad)					-0.34	-2.30**			-0.35	-2.10**
Cancer detection and diagnosis research					0.36	1.54			0.21	0.80
Cancer treatment research					0.38	1.60			0.16	0.59
Cancer biology research					0.63	2.10**			0.67	2.06**
Prior funding decisions										
Initial commitment (portfolio)							0.22	2.50**	0.22	2.32**
Sequencing (portfolio)							-0.02	-0.27	-0.02	-0.24
Fit (portfolio)							0.35	2.31**	0.28	1.79*
Control variables:										
Non-woman-owned	0.17	0.57	0.25	0.92	0.21	0.77	0.27	1.02	0.09	0.30
Non-minority-owned	0.17	0.41	0.10	0.25	0.12	0.31	0.01	0.02	0.01	0.03
Non-HubZone-owned	-0.26	-0.56	-0.38	-0.96	-0.51	-1.30	-0.49	-1.26	-0.31	-0.69
Industry volatility	0.03	0.14	0.16	0.95	0.05	0.26	0.12	0.70	-0.11	-0.58
State innovativeness	0.01	0.18	0.00	0.01	0.00	-0.03	-0.01	-0.13	-0.05	-0.60
Firm age	0.09	0.72	-0.09	-0.93	-0.03	-0.40	0.06	0.73	0.15	1.08
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.17		0.07		0.10		0.11		0.27	
Adjusted R^2	0.05		0.01		0.04		0.06		0.11	

N= 239

*** $p<0.01$; ** $p<0.05$; * $p<0.1$

Table 8-4: Logit model results – full sample – DV: discontinuation

	(1) Observables		(2) Unobservables		(3) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:								
Role legitimacy								
Manager CEO	-0.13	-0.39					0.01	0.03
PI CEO	-1.06	-3.28***					-1.01	-2.98***
PI's firm tenure	0.30	1.16					0.37	1.43
Manager's technical experience	0.19	0.79					0.26	1.04
PI's technical experience	-0.22	-0.93					-0.23	-0.93
Manager's entrepreneurial experience	-0.04	-0.17					-0.08	-0.28
PI's entrepreneurial experience	-0.01	-0.02					-0.07	-0.26
Resource legitimacy								
Manager's elite education	0.03	0.16					0.02	0.10
PI's elite education	0.10	0.57					0.17	0.96
Manager's MBA	0.15	0.30					0.12	0.22
PI's MBA	-1.17	-1.32					-1.19	-1.25
Manager's PhD	0.24	0.49					0.36	0.74
PI's PhD	0.07	0.09					-0.32	-0.42
Manager's professorship	-0.05	-0.12					-0.05	-0.11
PI's professorship	-0.57	-1.51					-0.58	-1.43
Intellectual legitimacy								
Manager's patents	0.31	1.54					0.31	1.52
PI's patents	0.19	1.08					0.14	0.79
Manager's publications	-0.25	-1.01					-0.23	-0.86
PI's publications	-0.24	-1.32					-0.28	-1.29
Abstract readability	-0.07	-0.53					-0.09	-0.63
Efficacy								
Project duration	0.33	2.45**					0.37	2.51**
Invention activity	-0.31	-1.82*					-0.65	-3.06***
Capabilities								
R&D capability			-0.05	-0.45			0.00	0.00
Managerial capability			0.16	1.21			0.52	2.60***
Intellectual capability			-0.02	-0.15			0.10	0.45
Project appeal								
Project scope (broad)					0.14	0.56	0.07	0.22
Cancer detection and diagnosis research					0.82	2.18**	0.90	1.95*
Cancer treatment research					0.91	2.36**	0.72	1.56
Cancer biology research					0.92	1.83*	0.98	1.67
Prior funding decisions								
Initial commitment (project)					0.03	0.23	-0.04	-0.26
Control variables:								
Non-woman-owned	-0.24	-0.42	0.14	0.30	0.02	0.05	-0.45	-0.75
Non-minority-owned	-0.20	-0.26	-0.26	-0.41	-0.30	-0.47	-0.32	-0.39
Non-HubZone-owned	0.50	0.78	1.03	1.92	0.95	1.76*	0.69	1.02
Industry volatility	-0.21	-0.62	-0.25	-0.88	-0.35	-1.20	-0.34	-0.96
State innovativeness	0.24	1.63	0.21	1.74*	0.24	2.01**	0.28	1.81*
Firm age	-0.12	-0.62	-0.04	-0.29	0.03	0.22	-0.21	-0.99
Year dummies	Incl.		Incl.		Incl.		Incl.	
Pseudo R^2	0.19		0.09		0.10		0.22	

N= 360[35]

*** p<0.01; ** p<0.05; * p<0.1

[35] The sample size is smaller because the model omitted observations for which year cohort categories had an insufficient number of observations for the analysis. The same applies to the split sample models.

Table 8-5: Logit model results – cluster with no prior awards – DV: discontinuation

	(1) Observables		(2) Unobservables		(3) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:								
Role legitimacy								
Manager CEO	0.42	0.50					1.23	1.05
PI CEO	-1.51	-2.14**					-2.34	-2.01*
PI's firm tenure	0.72	1.14					0.96	0.91
Manager's technical experience	0.41	1.01					0.61	1.28
PI's technical experience	0.03	0.06					-0.37	-0.62
Manager's entrepreneurial experience	-0.14	-0.36					0.01	0.02
PI's entrepreneurial experience	-0.13	-0.25					-0.42	-0.46
Resource legitimacy								
Manager's elite education	-0.04	-0.08					0.04	0.07
PI's elite education	0.10	0.28					0.58	1.59
Manager's MBA	-0.35	-0.44					-0.82	-0.80
PI's MBA	-1.80	-1.23					-2.42	-1.39
Manager's PhD	-0.50	-0.63					-0.28	-0.22
PI's PhD	-0.02	-0.02					-0.63	-0.40
Manager's professorship	0.37	0.42					0.75	0.60
PI's professorship	-0.81	-0.81					-1.12	-0.69
Intellectual legitimacy								
Manager's patents	0.06	0.12					0.37	0.54
PI's patents	0.27	0.77					0.27	0.61
Manager's publications	-0.03	-0.05					-0.34	-0.38
PI's publications	-0.26	-0.80					0.24	0.42
Abstract readability	0.04	0.12					-0.22	-0.57
Efficacy								
Project duration	0.43	1.42					0.77	1.95*
Invention activity	-0.07	-0.17					-0.28	-0.55
Capabilities								
R&D capability			0.11	0.59			0.44	1.45
Managerial capability			-0.02	-0.07			0.62	1.31
Intellectual capability			-0.38	-1.52			-0.90	-1.51
Project appeal								
Project scope (broad)					-0.51	-1.06	-0.91	-1.32
Cancer detection and diagnosis research					1.21	1.67*	1.81	1.43
Cancer treatment research					1.39	1.92*	1.41	1.25
Cancer biology research					2.42	2.26**	4.17	2.37**
Prior funding decisions								
Initial commitment (project)					-0.12	-0.44	-0.17	-0.32
Control variables:								
Non-woman-owned	0.78	0.51	1.52	1.23	1.56	1.24	0.22	0.11
Non-minority-owned	-0.88	-0.50	-1.58	-1.08	-1.69	-1.11	-0.43	-0.20
Non-HubZone-owned	0.15	0.15	0.91	1.15	1.06	1.30	0.08	0.05
Industry volatility	-0.67	-0.92	-0.33	-0.69	-0.49	-1.00	-0.97	-1.02
State innovativeness	0.07	0.25	0.04	0.18	0.16	0.71	0.08	0.22
Firm age	-0.65	-1.51	-0.30	-1.19	-0.17	-0.73	-0.62	-0.93
Year dummies	Incl.		Incl.		Incl.		Incl.	
Pseudo R^2	0.24		0.13		0.15		0.35	

N= 124[36]

*** p<0.01; ** p<0.05; * p<0.1

[36] The estimates were pooled across 3 out of 5 imputed datasets because omitted categorical variables varied across imputed datasets.

Table 8-6: Logit model results – cluster with prior awards – DV: discontinuation

	(1) Observables		(2) Unobservables		(3-1) Distortions		(3-2) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:										
Role legitimacy										
Manager CEO	-0.47	-0.99							-0.49	-0.93
PI CEO	-1.14	-2.41**							-1.01	-2.02**
PI's firm tenure	0.15	0.40							0.46	1.20
Manager's technical experience	0.17	0.51							0.25	0.62
PI's technical experience	-0.44	-1.41							-0.47	-1.22
Manager's entrepreneurial experience	0.01	0.03							0.02	0.05
PI's entrepreneurial experience	0.20	0.62							0.06	0.17
Resource legitimacy										
Manager's elite education	0.07	0.25							0.06	0.19
PI's elite education	0.09	0.42							0.17	0.70
Manager's MBA	0.53	0.61							0.54	0.57
PI's MBA	-0.74	-0.72							-1.05	-0.86
Manager's PhD	0.39	0.55							0.71	0.99
PI's PhD	0.18	0.15							-0.31	-0.25
Manager's professorship	-0.02	-0.04							-0.11	-0.19
PI's professorship	-0.76	-1.49							-0.96	-1.72*
Intellectual legitimacy										
Manager's patents	0.55	2.02**							0.66	2.04**
PI's patents	0.18	0.76							0.08	0.31
Manager's publications	-0.33	-0.83							-0.36	-0.75
PI's publications	-0.36	-1.40							-0.43	-1.53
Abstract readability	-0.17	-0.88							-0.13	-0.65
Efficacy										
Project duration	0.22	1.23							0.32	1.58
Invention activity	-0.41	-1.72*							-0.78	-2.51**
Capabilities										
R&D capability			-0.22	-1.20					-0.28	-1.14
Managerial capability			0.21	1.22					0.61	1.93*
Intellectual capability			0.04	0.24					0.32	1.02
Project appeal										
Project scope (broad)					0.32	1.04			0.27	0.64
Cancer detection and diagnosis research					0.66	1.37			0.43	0.65
Cancer treatment research					0.72	1.46			0.42	0.62
Cancer biology research					0.38	0.63			-0.22	-0.27
Prior funding decisions										
Initial commitment (project)							0.04	0.29	0.04	0.21
Initial commitment (portfolio)							0.01	0.05	-0.11	-0.47
Sequencing (portfolio)							-0.32	-2.12**	-0.24	-1.22
Fit (portfolio)							-0.01	-0.04	0.28	0.66
Control variables:										
Non-woman-owned	-0.57	-0.78	-0.04	-0.07	-0.23	-0.40	-0.17	-0.31	-0.35	-0.39
Non-minority-owned	-0.13	-0.12	0.17	0.21	0.11	0.14	0.43	0.54	-0.33	-0.28
Non-HubZone-owned	0.19	0.17	0.85	1.07	0.78	0.98	0.88	1.10	0.41	0.34
Industry volatility	0.01	0.01	-0.27	-0.71	-0.34	-0.88	-0.31	-0.81	-0.09	-0.17
State innovativeness	0.40	2.00**	0.27	1.68*	0.32	2.04**	0.33	2.08**	0.53	2.21**
Firm age	-0.01	-0.02	0.01	0.07	0.09	0.51	0.15	0.80	-0.26	-0.75
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.	
Pseudo R^2	0.24		0.11		0.11		0.12		0.30	

N= 236

*** p<0.01; ** p<0.05; * p<0.1

Relationship between Top Management Team Legitimacy and Funding Allocation Decisions

H2-1a: More observable signals of role legitimacy, resource legitimacy and intellectual legitimacy have a positive effect on the magnitude of initial funding commitment.

Testing Hypothesis 2-1a demonstrates mixed support for the predicted relationship between TMT legitimacy and the magnitude of initial funding commitment, and inter- and intra-variations exist for distinct categories of legitimacy signals within different samples.

The results of Model 1 of the full sample show that role legitimacy and intellectual legitimacy signals have an impact on the magnitude of initial funding commitment, while resource legitimacy has no impact. In the role legitimacy signal category, PI's organisational tenure and manager's entrepreneurial experience have a negative effect on the magnitude of initial funding ($\beta = -0.21$, $t = -2.38$) and ($\beta = -0.17$, $t = -1.82$) respectively, while PI's technical experience has a positive effect on the magnitude of initial commitment ($\beta = 0.15$, $t = 1.98$). In the intellectual legitimacy signal category, PI's patents have a positive effect ($\beta = 0.16$, $t = 2.36$), while PI's publications have a negative effect ($\beta = -0.18$, $t = -2.17$) on the magnitude of initial funding commitment. In other words, PI's technical competence (experience and inventive capacity) is associated with the higher amount of initial funding, while PI's tenure and academic competence are associated with the lower amount of initial funding. This suggests that PI's technical expertise is a strong signal of legitimacy that the top scientist within the team has relevant task-specific skills to successfully develop an innovation project. PI's longer tenure, on the other hand, informs investors' that the scientist is prone to the 'status quo', making breakthrough innovation less likely to occur. High publication activity signals that the PI is a theoretician rather than a practitioner and dedicates a significant amount of time to academic research, therefore has lower chances of converting a project into a commercial success. The negative albeit weak effect of manager's entrepreneurial experience is counterintuitive. It may be, that investors deliberately allocate smaller amounts of initial funding to firms with higher entrepreneurial credentials knowing that they already have the necessary social capital for potential commercial success. In the full model, PI's technical experience and manager's entrepreneurial experience become statistically insignificant, but remaining variables continue to be significant.

For firms with no prior awards in Model 1, the effect PI's organisational tenure has a weak negative effect ($\beta = -0.35$, $t = -1.92$) and PI's professorship a strong positive effect ($\beta = 0.47$, $t = 2.24$) on the magnitude of initial commitment, representing role legitimacy and resource legitimacy respectively. As expected, the presence of top academic scientists in the team signals credibility and access to a network of scientific resources and therefore helps attract a higher amount of initial funding. The independent variables remain significant in the full model.

For firms with prior awards in Model 1, intellectual legitimacy bears the strongest weight on initial funding commitment, with PI's patents having a strong and positive association (β = 0.19, t = 1.99) and PI's publications having a weak negative association (β = -0.22, t = -1.86). This indicates that PIs who engage in applied research as opposed to basic academic research have better chances of receiving higher initial funding. Additionally, PI's technical experience which forms part of the role legitimacy category has a weak positive effect on initial funding (β = 0.20, t = 1.75), which confirms the above finding that overall technical expertise of the lead scientist tends to be favourably perceived by investors. Nevertheless, the latter independent variable is insignificant in the full model.

H2-1b: More observable signals of role legitimacy, resource legitimacy and intellectual legitimacy decrease the likelihood of funding discontinuation.

Results of Hypothesis 2-1b testing show weak support that observable signals of legitimacy decrease the likelihood of discontinuation. Statistically significant independent variables are identical in Model 1 and Model 4.

In the full sample, only one indicator of the role legitimacy category is statistically significant, namely PI as a CEO decreases the likelihood of discontinuation (β = -1.06, t = -3.28). Likewise, in the cluster with no prior awards, PI as a CEO has a significant negative effect on discontinuation (β = -1.51, t = -2.14). In addition to the strong significant effect of the same predictor (β = -1.14, t = -2.41), in the cluster of firms with no prior awards, manager's patents increase the likelihood of discontinuation (β = 0.55, t = 2.02). For all samples, executive's functional role as a PI increases chances for continued funding of innovation projects, which indicates that CEO's participation in technical roles is positively viewed by investors. The positive effect of manager's inventive capacity on the likelihood of discontinuation may be explained by the fact that patenting is a technical task and is considered by investors to be outside the scope of direct managerial responsibilities, which should instead be focused on strategic aspects of venture development. Hence, manager's high patenting activity signals to the capital market that functional roles within the team are misaligned.

Overall, the results demonstrate that observable signals of TMT legitimacy are weak predictors of funding allocation decisions, so support for Hypothesis 2-1 is limited.

Relationship between Efficacy and Funding Allocation Decisions

H2-2: More recent signals of efficacy have a stronger effect on the likelihood of funding discontinuation than signals of legitimacy.

There is a strong overall support for Hypotheses 2-2, as observed from the results of the full sample analysis in Model 1, which reveal that both indicators of efficacy have a statistically significant impact on discontinuation and directions of relationships match initial expectations. Project duration (β = 0.33, t = 2.45) increases the likelihood of discontinuation, whereas invention activity (β = -0.31, t = 1.82) decreases the likelihood of funding discontinuation. The results are supported by the full model.

The effect of efficacy signals on Phase II funding allocation decision is less prominent in the split sample analysis. In Model 4, project duration (β = 0.77, t = 1.95) weakly increases the likelihood of discontinuation for firms with no prior awards, whereas invention activity (β = -0.78, t = -2.51) decreases the likelihood of funding discontinuation for firms with prior awards. This finding suggests that when evaluating efficacy credentials, investors expect new programme participants to demonstrate their ability to keep experimentation time low, and experienced programme participants to develop patentable technologies as a result of Phase I allocated funding. Overall, the findings suggest that the temporal relevance of post-funding efficacy has an impact on investment decision-making as such flow-type signals convey up-to-date operational information and help update investors' perspectives on firms' potential.

Relationship between Capabilities and Funding Allocation Decisions

H2-3a: In contrast to more observable signals of legitimacy, less observable signals of R&D, intellectual and managerial capability have no effect on the magnitude of initial funding commitment.

Testing Hypothesis 2-3a in Model 2 and Model 4 demonstrates strong support for the predicted relationship between capabilities and the magnitude of initial funding commitment in both full and split samples.

H2-3b: In contrast to more observable signals of legitimacy, less observable signals of R&D, intellectual and managerial capability have no effect on the likelihood of funding discontinuation.

Likewise, as per Hypothesis 2-3b, capabilities have no effect on the likelihood funding discontinuation in both full and split samples. Only in Model 4 of the full sample managerial capability has a strong positive effect on discontinuation and a weak positive effect in the cluster with prior awards. The positive effect on discontinuation could perhaps suggest that firms with strong managerial capability opt from applying for Phase II funding.

Overall, the findings related to Hypothesis 2-3 indicate that despite the expected positive impact of capabilities on firms' future potential for success, capabilities have no direct effect on funding allocation decisions because they happen inside the 'black box' of the firm, and hence are difficult to observe as signals without explicitly measuring them. This finding offers support for both signalling theory and attention-based view of the firm. It confirms that for signals to be efficacious, they need to be visible to outsiders, while decision-makers only respond to those cues which they can notice.

Effect of Attention-Distorting Signal Categories on Funding Allocation Decisions

H2-4a: Directly relevant project appeal characteristics have a stronger effect on the magnitude of initial funding commitment than legitimacy signals.

The findings of Model 3 offer support for Hypothesis 2-4a. Both indicators representing project appeal category are statistically significant in the full sample and the cluster with prior awards. Contrary to the initial expectation, broad project scope diminishes the magnitude of initial funding commitment in the full sample (β = -0.30, t= -2.81) and in the sample with prior awards (β = -0.34, t = -2.30). Moreover, projects focused on cancer biology research are more likely to receive higher initial funding commitment than projects focused on cancer cause and prevention research, as seen in the full sample (β = 0.58, t = 2.54) and in the sample with prior awards (β = 0.63, t = 2.10). Additionally, as evident by the results of Model 4, the presence of project appeal characteristics diverts decision-makers' attention from intended legitimacy signals, as demonstrated by their lower weights in the full model. No support for Hypothesis 2-4a is offered by results of the cluster with no prior awards.

Overall, the findings suggest that investors have funding agenda in place which favours projects with a narrow scope and dedicated to cancer biology research. Hence, these characteristics are stronger cues in comparison to other indirect cues such as legitimacy and efficacy as they are directly relevant to evaluators' agenda. Hence, decision-makers' attention is concentrated in communication channels located in application forms, making them notice and react to specific project characteristics, applying higher weights to those factors they are looking for.

H2-4b: Directly relevant project appeal characteristics have a stronger effect on the likelihood of funding discontinuation than legitimacy signals.

Partial support for Hypothesis 2-4b is observed in the full sample and the sample of firms with no prior awards. Although the effect of project scope is statistically insignificant, the membership of projects in specific categories increases their likelihood of funding discontinuation. Specifically, as seen in Model 3-1, projects focused on cancer detection and diagnosis research (β = 0.82, t = 2.18; β = 1.21, t = 1.67), cancer treatment research (β = 0.91, t = 2.36; β = 1.39, t = 1.92), and cancer biology research (β = 0.92, t = 1.83; β = 2.42, t = 2.26) are more likely to experience funding discontinuation than projects focused on cancer cause and prevention research, as seen in the full sample and the sample of firms with no prior awards, respectively. However, the effect of these project categories is less profound in the full model. Also, project appeal characteristics have no effect on discontinuation among firms with prior awards.

Overall, the findings mostly confirm Hypothesis 2-4 that project appeal characteristics have a strong effect on funding allocation decisions and also divert decision-makers' attention from other categories of signals. In other words, evaluators pay more attention to those projects which meet their internal funding agenda.

H2-5a: Previous funding allocation decisions have a stronger positive effect on the magnitude of initial funding commitment than legitimacy signals.

Testing Hypothesis 2-5a in Model 3-2 shows evidence for the distorting effect of prior portfolio-level funding allocation decisions. Higher prior portfolio-level initial commitment ($\beta = 0.22$, $t = 2.50$) and prior fit of funding decisions ($\beta = 0.35$, $t = 2.31$) have a strong and positive effect on the magnitude of initial commitment. This suggests that investors follow their prior decision-making patterns, and when they allocated higher amounts of initial commitment, they will also do so for the new option. Also, matching of previous funding decisions in line with the ROR logic is also positively associated with the magnitude of initial commitment. The results remain statistically significant in the full model.

H2-5b: Previous funding allocation decisions have a stronger negative effect on the likelihood of funding discontinuation than legitimacy signals.

There is partial support for Hypothesis H2-5b at the portfolio-level. The results show that high sequencing rate of previous projects in the portfolio ($\beta = -0.32$, $t = -2.12$) reduces the likelihood of discontinuation of new projects. In other words, when investors allocated funding to Phase II projects in the past, they will also do so in the future. However, the effect of sequencing is insignificant in the full model. Also, there is no effect of the magnitude of initial funding commitment to an individual project.

8.3 Robustness Checks

As in Part I analysis, robustness checks were performed to check for potential negative effects of heteroscedastic data. To control for this problem, robust standard errors were estimated for each model using the ‘vce’ specification in STATA, which generated more robust confidence intervals and p-values.

The results of robustness checks of the OLS regression model on initial commitment are reported in Appendix 27 for the full sample, Appendix 28 for the cluster with no prior awards and Appendix 29 for the cluster with prior awards. Results of robustness checks of the Logit regression model on discontinuation appear in Appendix 30 for the full sample, Appendix 31 for the cluster with no prior awards and Appendix 32 for the cluster with prior awards.

The results of robustness checks are in line with the results reported in the main model. Independent variables explaining variance in the dependent variables remained statistically significant under robust standard errors, confirming the validity of hypotheses testing.

8.4 Summary

The results presented in this chapter contribute to the understanding of venture funding decision-making process. Specifically, they provide insights into the funding allocation process of the government capital providers.

Table 8-7 presents a summary of the findings from OLS and Logit models in relation to hypotheses tested in Part II analysis. Although overall the effects of signals are rather low on both funding allocation outcomes, partial support for hypotheses is still evident, and a number of important conclusions can be drawn.

Table 8-7: Summary of Part II hypotheses testing results

Hypothesis	Hypothesised relationship	Hypothesised effect	Full sample	Cluster: with no prior awards	Cluster: with prior awards
H2-1a	Legitimacy signals -> Initial commitment	Positive	PS, CF	PS, CF	PS, CF
H2-1b	Legitimacy signals -> Discontinuation	Negative	PS	PS	PS, CF
H2-2	Efficacy signals -> Discontinuation	Both	S	NS	PS
H2-3a	Capability signals -> Initial commitment	No effect	S	S	S
H2-3b	Capability signals -> Discontinuation	No effect	S	S	S
H2-4a	Project appeal signals -> Initial commitment	Positive	S, CF	NS	S, CF
H2-4b	Project appeal signals -> Discontinuation	Positive	PS	PS	NS
H2-5a	Distortion signals -> Initial commitment	Positive	NA	NA	S
H2-5b	Distortion signals -> Discontinuation	Negative	NA	NA	PS

Notes: S – supported, NS – not supported, PS – partially supported, CF – contrary finding, NA – not applicable;
*** p<0.01; ** p<0.05; * p<0.1

First, TMT legitimacy signals have mixed effects on funding allocation outcomes. In isolation, role legitimacy and intellectual legitimacy affect the magnitude of initial funding commitment of all firms in the sample. The results show that generally PI's technical and inventive competence helps attract a higher amount of initial funding, while PI's tenure and academic competence decrease the amount of initial funding. A similar pattern is observed among firms with prior awards. This suggests that investors have positive perceptions of TMTs in which top scientists have proven functional skills, manifested by technical experience and patents, are not absorbed in excessive publication activity and can bring in fresh perspectives to the NPD process from other organisations. In contrast, for firms with no prior awards, resource legitimacy is the most important factor, with PI's professorship being the strongest positive signal which magnifies initial funding commitment. The finding indicates that for existing award holders, narrow practical expertise in a relevant technical field is the most sought after attribute. New award holders, on the other hand, can signal their potential with the involvement of high-status academic scientists in the team, who contribute not only legitimate human capital but also social capital acquired through a network of institutional affiliations. At the same time, the explanatory power of legitimacy signals is weaker in relation to the funding discontinuation decision. For all samples, role legitimacy is a single strongest category. Specifically, executive's functional role as a PI minimises chances of funding discontinuation, suggesting that CEO's participation in technical roles is positively perceived by investors.

Second, the likelihood of funding discontinuation is strongly affected by firms' efficacy. In particular, new award holders' ability to minimise project duration and existing award holders' ability to commercialise technical knowledge by acquiring patents increases their chances for continued financial support from the government.

Third, more visible signals of TMT legitimacy and efficacy have a stronger overall effect on funding allocation outcomes, while subtler signals of capabilities have no effect as they are less visible, confirming the propositions of signalling theory and ABV that only observable information can trigger action of decision-makers.

Fourth, there is evidence that project appeal characteristics tend to affect the funding allocation decisions. The latter means that allocation of funds is hugely driven by the government's research needs and priorities, rather than the firms' perceived ability to carry out projects successfully based on their legitimacy characteristics.

Finally, previous portfolio-level funding outcomes affect current funding outcomes. Specifically, higher previous initial commitment and fit of funding allocation decisions are associated with a higher initial commitment for the new project. On the other hand, higher previous propensity to sequence projects in the portfolio increases chances of continued funding of new projects. These findings indicate that funders use their prior funding allocation decisions as cues to screen firms and allocate grants out of inertia. These findings suggest that investment decision-making is often informed by intuitively formulated heuristics which results in evaluation bias (Zacharakis and Shepherd 2001) and discrepancies between 'in use' and 'espoused' decision rules (Shepherd 1999).

In sum, the results of empirical inquiry confirm the primary expectations of signalling theory and attention-based view of the firm. Financial valuations often take account of firms' both tangible and intangible assets (Busenitz et al. 2005). Although desirable, evaluation of different types of assets requires higher time and financial resources (Harvey and Lusch 1995). To be effective, a signal must be able to communicate differences among very competent and less competent new venture teams (Busenitz et al. 2005). However, when competencies are specific, complex and rare, assessing such differences becomes difficult (Gimmon and Levie 2010).

Signals are most credible when they indicate actions which are difficult to costlessly replicate by less competent agents (Morris 1987). As Tornikoski and Newbert (2007) pointed, markets rely less on passive resource endowments than on the proactive search for legitimacy, concluding that nascent firms can change external evaluators' perceptions of organisational capabilities and credibility by engaging in operational behaviours. Recent research demonstrated that for finance providers to microenterprises, firms' behavioural intentions are more meaningful signals than their static attributes, and when lenders do not expect loan repayments, signals of legitimacy and trust become less important to the decision-making process (Moss et al. 2015).

Empirical evidence presented here confirms previous findings that static signals of conforming legitimacy are less powerful in influencing investors' decision-making than flow signals of strategic legitimacy (Tornikoski and Newbert 2007; DeKinder and Kohli 2008). That is, from investors' perspective, what economic agents do is more important than what backgrounds and capabilities they have. As a whole, financial decision-makers focus their attention on factors which they perceive to be more relevant to the evaluation process. Subsequently, more salient characteristics of projects and firms bear higher weights on funding allocation outcomes than observable characteristics, whereas less observable characteristics barely have any impact at all.

Chapter 9 - Results & Discussion (III): Testing Hypotheses of the Complementarities of Real Options Reasoning and Signalling Models

9.1 Introduction

This chapter presents the findings of simultaneous equations of Part III analysis. The estimates were produced under SUR (GLS) procedure in STATA using standardised data.
Like in Part I analysis, the Breusch-Pagan test of independence of residuals was statistically significant at $p<0.001$ for all systems of equations, indicating that SUR is a comprehensive modelling procedure producing more robust estimations.

Under SUR GLS, R^2 for individual equations took values between 0.24 and 0.68, while adjusted R^2 ranged between 0.14 and 0.52. This shows that independent variables explain a significant proportion of variance in the dependent variables, although the model fit statistic exhibits significant heterogeneity between individual equations and between samples.

The forthcoming sections first report the results of full models and then interpret the findings in light of the hypotheses. Next, the validity of results is confirmed using the robustness checks and sensitivity analyses. To conclude the chapter, the main insights of Part III analysis are summarised.

9.2 Hypotheses Testing

Table 9-1 reports estimated coefficients and t-values for the full sample SUR regression model of Part III analysis, Table 9-2 for the cluster with no prior awards and Table 9-3 for the cluster with prior awards. Next, the results are interpreted in relation to individual hypotheses.

Table 9-1: System of equations (SUR) results – full sample

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level funding												
Initial commitment	-0.17	-2.99***	-0.22	-4.16***	-0.03	-0.48	0.03	0.60	0.02	0.38	0.03	0.66
Discontinuation	0.00	0.01	0.01	0.05	-0.17	-1.56	0.07	0.70	0.03	0.35	-0.26	-2.60***
Fit	-0.10	-0.89	-0.13	-1.25	-0.05	-0.47	-0.05	-0.53	-0.08	-0.93	-0.05	-0.56
Portfolio-level funding												
Fit	0.22	1.92*	0.26	2.49**	0.08	0.78	-0.05	-0.48	-0.03	-0.27	0.07	0.70
Role legitimacy												
Manager CEO	-0.13	-0.82	-0.17	-1.04	-0.05	-0.38	-0.35	-2.42	-0.36	-2.50**	-0.10	-0.78
PI CEO	0.05	0.36	0.05	0.37	-0.15	-1.13	0.08	0.68	0.06	0.54	-0.11	-0.97
PI's firm tenure	-0.35	-4.00***	-0.34	-4.24***	-0.08	-0.85	-0.19	-2.63**	-0.19	-2.87***	0.02	0.23
Manager's technical experience	0.06	0.49	0.08	0.57	0.10	1.17	-0.03	-0.35	-0.05	-0.66	0.13	1.24
PI's technical experience	0.06	0.64	0.09	1.15	0.00	-0.03	-0.03	-0.47	-0.05	-0.72	-0.07	-0.96
Manager's entrepreneurial experience	-0.02	-0.16	-0.05	-0.38	-0.03	-0.30	0.03	0.33	0.02	0.25	0.04	0.45
PI's entrepreneurial experience	0.12	1.51	0.07	0.84	0.01	0.14	-0.12	-1.80*	-0.09	-1.34	-0.11	-1.47
Resource legitimacy												
Manager's elite education	-0.07	-0.97	-0.04	-0.55	-0.02	-0.39	0.12	1.57	0.11	1.42	0.11	1.81*
PI's elite education	0.05	0.74	0.07	1.10	0.05	0.84	-0.03	-0.34	0.02	0.40	0.00	0.06
Manager's MBA	0.42	1.91*	0.41	2.09*	0.16	0.68	-0.05	-0.31	0.03	0.21	-0.24	-1.25
PI's MBA	-0.29	-1.21	-0.34	-1.40	0.04	0.14	-0.22	-1.08	-0.23	-1.14	0.19	0.88
Manager's PhD	0.02	0.12	0.10	0.47	0.11	0.59	0.05	0.36	0.09	0.58	-0.11	-0.72
PI's PhD	-0.23	-0.65	-0.12	-0.50	-0.06	-0.22	-0.39	-0.97	-0.33	-1.03	-0.01	-0.05
Manager's professorship	-0.11	-0.64	-0.13	-0.75	0.03	0.17	-0.10	-0.79	-0.01	-0.10	0.02	0.13
PI's professorship	-0.09	-0.70	-0.04	-0.31	-0.41	-2.95***	0.13	1.02	0.13	0.92	-0.33	-2.72***
Intellectual legitimacy												
Manager's patents	-0.06	-0.77	-0.06	-0.85	0.02	0.24	-0.11	-1.75*	-0.06	-0.90	-0.01	-0.09
PI's patents	-0.06	-0.89	-0.05	-0.75	0.08	1.23	-0.03	-0.60	0.01	0.15	0.13	2.23**
Manager's publications	0.03	0.27	-0.01	-0.08	-0.13	-1.22	0.07	0.96	0.02	0.30	-0.04	-0.32
PI's publications	0.03	0.36	0.00	0.05	0.15	1.78*	0.07	1.08	0.09	1.30	0.17	2.12**
Abstract readability	0.02	0.40	-0.01	-0.14	-0.01	-0.20	0.02	0.41	0.00	0.00	0.00	-0.06
Efficacy												
Project duration	-0.14	-2.31**	-0.18	-3.10***	-0.12	-2.16**	-0.05	-0.97	-0.09	-1.78**	0.02	0.42
Invention activity	0.12	1.58	0.08	1.15			0.18	2.36**	0.19	2.66**		
Capabilities												
R&D capability	-0.01	-0.13	0.00	-0.02	0.03	0.44	0.01	0.08	0.01	0.21	0.12	1.85*
Managerial capability	0.09	0.85	0.03	0.33	0.20	2.10**	-0.03	-0.32	-0.01	-0.11	0.22	2.06*
Intellectual capability	-0.09	-1.33	-0.02	-0.38	0.08	1.18	-0.02	-0.34	-0.01	-0.23	0.08	1.30
R&DCapXManCap	0.00	-0.06	0.00	0.03	-0.02	-0.40	0.05	1.03	0.02	0.35	-0.01	-0.22
R&DCapXIntCap	0.01	0.06	-0.01	-0.14	0.06	0.74	0.01	0.18	-0.01	-0.18	0.03	0.45
IntCapXManCap	0.00	0.03	0.07	0.85	0.01	0.09	0.09	1.26	0.08	1.17	0.14	1.73*
Control variables:												
Non-woman-owned	0.48	1.49	0.51	2.05*	0.03	0.16	0.24	0.88	0.33	1.28	-0.08	-0.46
Non-minority-owned	-0.40	-0.91	-0.52	-1.47	0.16	0.57	-0.39	-1.18	-0.41	-1.24	0.30	1.17
Non-HubZone-owned	-0.24	-0.75	-0.28	-0.99	-0.16	-0.67	0.00	0.01	0.00	-0.01	-0.03	-0.15
Industry volatility	-0.22	-2.85***	-0.16	-2.19**	-0.05	-0.71	-0.07	-1.07	0.01	0.16	-0.04	-0.62
State innovativeness	-0.09	-1.56	-0.09	-1.79*	0.01	0.19	-0.02	-0.47	-0.02	-0.51	0.07	1.41
Firm age	0.14	1.53	0.04	0.47	-0.20	-2.52**	0.52	6.79***	0.53	8.16***	-0.02	-0.36
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.27		0.31		0.24		0.49		0.50		0.38	
Adjusted R^2	0.17		0.22		0.14		0.42		0.43		0.30	

N= 367; *** $p<0.01$; ** $p<0.05$; * $p<0.1$

Table 9-2: System of equations (SUR) results – cluster with no prior awards

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level funding												
Initial commitment	-0.32	-2.42**	-0.34	-3.77***	0.13	0.79	-0.10	-1.10	-0.14	-1.56	0.13	1.31
Discontinuation	-0.10	-0.41	-0.11	-0.75	-0.19	-0.76	-0.05	-0.29	-0.13	-1.00	-0.09	-0.59
Fit	-0.06	-0.37	0.03	0.22	-0.18	-0.74	-0.05	-0.47	-0.01	-0.07	-0.12	-0.83
Role legitimacy												
Manager CEO	-0.08	-0.37	0.01	0.09	0.22	0.76	-0.07	-0.55	-0.02	-0.12	0.09	0.45
PI CEO	-0.08	-0.39	-0.15	-0.97	-0.82	-2.42**	0.02	0.17	-0.17	-1.15	-0.44	-2.09**
PI's firm tenure	-0.41	-1.70	-0.29	-1.80*	-0.34	-1.22	-0.33	-2.33**	-0.34	-2.30**	-0.26	-1.55
Manager's technical experience	-0.06	-0.32	-0.04	-0.36	0.29	1.55	-0.08	-0.63	-0.10	-0.90	0.12	0.98
PI's technical experience	-0.15	-0.87	-0.01	-0.13	-0.08	-0.39	-0.11	-1.28	-0.06	-0.75	-0.04	-0.35
Manager's entrepreneurial experience	0.35	1.79*	0.17	1.16	0.05	0.18	0.23	1.78*	0.17	1.12	0.05	0.31
PI's entrepreneurial experience	0.10	0.55	0.01	0.09	0.03	0.18	0.12	1.24	0.13	1.20	0.06	0.51
Resource legitimacy												
Manager's elite education	0.14	1.27	0.12	1.37	0.00	0.00	0.08	0.96	0.12	1.10	-0.05	-0.48
PI's elite education	0.06	0.56	0.11	1.48	-0.06	-0.42	0.04	0.50	0.10	1.14	-0.04	-0.47
Manager's MBA	0.52	1.90*	0.29	1.50	0.24	0.77	0.30	1.83*	0.20	0.98	0.12	0.62
PI's MBA	0.40	0.99	0.56	1.94*	0.26	0.39	0.02	0.10	0.30	1.05	-0.02	-0.05
Manager's PhD	-0.36	-1.33	-0.30	-1.28	0.01	0.02	-0.20	-1.17	-0.34	-1.54	-0.01	-0.05
PI's PhD	-0.06	-0.12	0.18	0.74	-0.13	-0.25	-0.02	-0.07	0.17	0.76	-0.12	-0.40
Manager's professorship	0.30	1.05	0.17	0.88	0.45	1.25	0.16	0.81	0.14	0.67	0.24	1.09
PI's professorship	0.20	0.73	0.24	1.15	-0.70	-1.89*	0.08	0.49	0.12	0.66	-0.45	-2.11**
Intellectual legitimacy												
Manager's patents	0.00	-0.01	0.02	0.13	-0.01	-0.04	-0.03	-0.26	-0.01	-0.04	-0.03	-0.22
PI's patents	0.16	0.95	0.13	1.32	0.48	2.91***	0.10	0.95	0.16	1.66	0.29	2.79***
Manager's publications	0.29	1.14	0.23	1.19	-0.15	-0.69	0.22	1.50	0.27	1.52	-0.02	-0.17
PI's publications	0.11	0.69	0.04	0.33	0.16	0.74	0.06	0.76	0.04	0.53	0.06	0.48
Abstract readability	0.10	0.98	0.03	0.48	-0.13	-1.04	0.09	1.40	0.09	1.31	-0.08	-1.06
Efficacy												
Project duration	-0.18	-1.35	-0.17	-2.27**	-0.46	-3.12***	-0.03	-0.30	-0.08	-1.12	-0.27	-2.93***
Invention activity	-0.01	-0.04	-0.01	-0.05			-0.06	-0.54	-0.02	-0.21		
Capabilities												
R&D capability	0.12	0.80	0.09	0.91	0.34	1.91*	0.02	0.26	0.05	0.46	0.19	1.77*
Managerial capability	0.86	2.90**	0.54	3.47***	0.34	0.79	0.58	3.20***	0.61	3.77***	0.14	0.57
Intellectual capability	-0.37	-1.97*	-0.15	-1.20	-0.01	-0.06	-0.24	-2.15**	-0.16	-1.37	-0.02	-0.16
R&DCapXManCap	-0.24	-1.77*	-0.22	-2.46**	0.35	1.94*	-0.15	-1.69	-0.24	-2.95***	0.26	2.41**
R&DCapXIntCap	-0.21	-1.81*	-0.17	-2.23**	-0.15	-1.13	-0.06	-0.95	-0.11	-1.57	-0.05	-0.66
IntCapXManCap	-0.38	-1.38	-0.04	-0.32	-0.66	-2.12**	-0.26	-1.51	-0.06	-0.44	-0.37	-1.96*
Control variables:												
Non-woman-owned	0.41	0.95	0.67	2.45**	-0.41	-0.75	0.09	0.27	0.52	2.03**	-0.30	-0.92
Non-minority-owned	-0.38	-0.47	-0.46	-0.95	0.76	1.08	-0.10	-0.22	-0.23	-0.49	0.58	1.39
Non-HubZone-owned	0.02	0.05	-0.10	-0.38	-0.37	-0.77	0.02	0.05	-0.13	-0.48	-0.12	-0.42
Industry volatility	-0.11	-0.62	-0.07	-0.50	-0.07	-0.35	-0.04	-0.34	0.00	-0.03	0.00	0.04
State innovativeness	-0.02	-0.20	-0.02	-0.30	0.14	1.31	-0.01	-0.13	-0.03	-0.42	0.10	1.45
Firm age	0.47	2.50**	0.35	2.91**	-0.03	-0.14	0.31	2.75**	0.35	2.95**	0.02	0.22
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.63		0.68		0.44		0.56		0.64		0.45	
Adjusted R^2	0.44		0.52		0.16		0.34		0.46		0.17	

N= 128; *** p<0.01; ** p<0.05; * p<0.1

Table 9-3: System of equations (SUR) results – cluster with prior awards

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Independent variables:												
Project-level funding												
Initial commitment	-0.05	-0.96	-0.09	-1.84*	-0.03	-0.70	0.08	1.20	0.08	1.28	0.00	0.02
Discontinuation	0.12	1.10	0.08	0.74	0.01	0.11	0.16	1.29	0.09	0.72	-0.18	-1.48
Fit	-0.02	-0.21	-0.07	-0.76	-0.06	-0.70	-0.13	-1.16	-0.19	-1.87	-0.09	-0.75
Portfolio-level funding												
Initial commitment	-0.12	-2.00**	-0.14	-2.21**	-0.10	-1.78*	-0.05	-0.67	-0.02	-0.27	-0.03	-0.46
Sequencing	-0.18	-3.73***	-0.25	-4.94***	-0.14	-3.29***	-0.02	-0.44	-0.03	-0.53	-0.01	-0.25
Fit	0.15	1.55	0.13	1.28	0.12	1.39	-0.15	-1.28	-0.18	-1.46	0.13	1.06
Role legitimacy												
Manager CEO	-0.16	-1.03	-0.27	-1.69	-0.07	-0.59	-0.48	-2.55**	-0.54	-2.97**	-0.03	-0.20
PI CEO	0.09	0.73	0.10	0.84	0.12	1.09	0.15	0.78	0.14	0.81	0.17	1.10
PI’s firm tenure	-0.21	-3.03***	-0.27	-3.43***	-0.04	-0.50	-0.14	-1.55	-0.14	-1.74*	0.09	0.93
Manager’s technical experience	-0.02	-0.26	-0.01	-0.12	0.03	0.44	-0.06	-0.60	-0.09	-0.99	0.23	1.53
PI’s technical experience	0.05	0.74	0.05	0.68	0.01	0.07	0.02	0.19	-0.03	-0.32	-0.10	-0.95
Manager’s entrepreneurial experience	-0.12	-0.94	-0.10	-0.76	-0.01	-0.16	-0.02	-0.17	-0.01	-0.08	0.02	0.23
PI’s entrepreneurial experience	0.04	0.57	0.03	0.46	0.00	0.04	-0.29	-3.23***	-0.24	-2.78***	-0.19	-1.72
Resource legitimacy												
Manager’s elite education	0.05	0.66	0.08	0.94	0.05	0.78	0.14	1.33	0.14	1.51	0.15	1.57
PI’s elite education	-0.06	-0.84	-0.04	-0.59	0.03	0.66	-0.10	-1.00	-0.05	-0.65	0.00	0.00
Manager’s MBA	0.08	0.38	0.09	0.40	-0.12	-0.60	-0.32	-1.37	-0.20	-0.86	-0.57	-2.24**
PI’s MBA	-0.34	-1.49	-0.46	-2.00*	-0.16	-0.75	-0.21	-0.78	-0.28	-1.08	0.06	0.18
Manager’s PhD	0.03	0.16	0.17	0.88	-0.04	-0.24	0.02	0.11	0.13	0.68	-0.30	-1.23
PI’s PhD	-0.47	-1.30	-0.41	-1.51	0.10	0.43	-0.58	-1.00	-0.57	-1.16	0.17	0.41
Manager’s professorship	0.00	0.00	0.03	0.19	-0.15	-1.13	-0.09	-0.52	0.07	0.40	-0.25	-1.50
PI’s professorship	-0.01	-0.06	0.02	0.10	-0.12	-1.04	0.19	1.10	0.16	0.95	-0.18	-1.16
Intellectual legitimacy												
Manager’s patents	0.02	0.21	0.03	0.39	0.05	0.74	-0.08	-0.99	-0.01	-0.07	-0.02	-0.19
PI’s patents	-0.04	-0.69	-0.05	-0.71	-0.02	-0.29	-0.04	-0.63	-0.02	-0.34	0.07	0.93
Manager’s publications	-0.04	-0.51	-0.11	-1.40	-0.03	-0.33	0.04	0.47	-0.05	-0.57	-0.01	-0.07
PI’s publications	0.03	0.51	0.04	0.56	0.15	2.39**	0.10	1.22	0.12	1.57	0.21	2.42**
Abstract readability	0.00	-0.02	-0.03	-0.52	0.00	0.08	-0.02	-0.40	-0.06	-1.04	0.02	0.37
Efficacy												
Project duration	-0.08	-1.46	-0.14	-2.55**	-0.01	-0.18	-0.05	-0.84	-0.08	-1.38	0.09	1.49
Invention activity	0.11	1.50	0.12	1.59			0.22	2.38**	0.25	2.97***		
Capabilities												
R&D capability	0.03	0.34	0.00	0.04	0.03	0.33	0.00	-0.03	-0.05	-0.48	0.19	1.98**
Managerial capability	-0.09	-0.99	-0.12	-1.38	0.09	0.92	-0.22	-1.99*	-0.21	-2.04**	0.17	1.13
Intellectual capability	-0.02	-0.32	0.01	0.16	0.05	1.03	0.00	0.03	0.00	-0.08	0.08	1.12
R&DCapXManCap	0.06	1.28	0.07	1.31	-0.02	-0.41	0.16	2.53**	0.14	2.21**	-0.02	-0.31
R&DCapXIntCap	0.03	0.38	0.02	0.22	0.11	1.44	0.05	0.50	0.05	0.48	0.06	0.54
IntCapXManCap	0.07	1.09	0.09	1.38	0.15	2.19**	0.14	1.84*	0.10	1.36	0.24	2.24**
Control variables:												
Non-woman-owned	0.16	0.47	0.10	0.35	0.10	0.63	0.34	1.09	0.29	0.95	0.08	0.38
Non-minority-owned	-0.25	-0.89	-0.43	-1.46	0.23	0.99	-0.48	-1.34	-0.56	-1.55	0.50	1.57
Non-HubZone-owned	-0.06	-0.25	-0.12	-0.43	0.09	0.36	0.01	0.02	0.04	0.12	-0.03	-0.08
Industry volatility	-0.13	-1.25	-0.05	-0.63	-0.08	-1.34	-0.13	-0.98	-0.01	-0.13	-0.12	-1.41
State innovativeness	-0.03	-0.61	-0.03	-0.61	-0.02	-0.45	-0.05	-0.89	-0.03	-0.59	0.02	0.38
Firm age	0.22	2.08	0.22	2.39**	-0.17	-1.94	0.62	4.83***	0.59	5.50***	-0.09	-0.81
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.40		0.43		0.37		0.59		0.59		0.50	
Adjusted R^2	0.25		0.30		0.23		0.50		0.49		0.39	

N= 239; *** p<0.01; ** p<0.05; * p<0.

Effect of Funding Allocation Outcomes on Long-term Performance in the Presence of Firm-level Factors

H3-1: Effects of ROR elements on investment yield and firm performance continue to remain significant in the presence of firm-level factors.

Table 9-4 compares the findings of Part I and Part III models. Overall, the effects of ROR elements on investment yield and firm performance continue to remain statistically significant in an extended model, thereby confirming Hypothesis 3-1.

The results further confirm the previous findings. First, the magnitude of initial commitment has a strong negative effect on investment yield and no effect on firm performance. Second, discontinuation has an overall strong negative effect on innovation performance, although the effect is no longer significant in the cluster with no prior awards. Third, fit of funding allocation decisions in line with the ROR logic has a positive effect on sales and employment yield at the portfolio-level. Fourth, high rate of funding sequencing has a strong negative effect on investment yield. Finally, for firms with prior awards, the addition of a new individual project to the portfolio has no effects on investment yield and firm performance, suggesting that new options are subadditive. Additionally, the results further confirm that ROR elements have a weak association with firm performance and innovation outcomes.

In sum, the results further confirm the robustness of the findings of Part I analysis and show overall support of the propositions of ROR. The magnitude and continuation of funding have a diminishing effect on return on investment, while consistent matching of funding decisions in line with prescriptions of the ROR logic across the entire portfolio of options has a positive impact on sales and employment yield.

Table 9-4: Comparison of Part I and Part III ROR theory hypotheses testing results

Hypothesis	Hypothesised relationship	Level	Full Sample				Firm Cluster: No prior awards				Firm Cluster: With prior awards			
			Part I	Part III			Part I	Part III			Part I	Part III		
			Result	β	t-value	Result	Result	β	t-value	Result	Result	β	t-value	Result
H1-1a	Initial commitment -> Sales Yield	Project	**S**	**-0.17**	**-2.99*****	**S**	**S**	**-0.32**	**-2.42****	**S**	NS	-0.05	-0.96	NS
H1-1b	Initial commitment -> Employment Yield	Project	**S**	**-0.22**	**-4.16*****	**S**	**S**	**-0.34**	**-3.77****	**S**	NS	-0.09	-1.84*	PS
H1-1c	Initial commitment -> Innovation Yield	Project	NS	-0.03	-0.48	NS	NS	0.13	0.79	NS	NS	-0.03	-0.70	NS
H1-1d	Initial commitment -> Sales Performance	Project	NS	0.03	0.60	NS	PS	-0.10	-1.10	NS	CF	0.08	1.20	NS
H1-1e	Initial commitment -> Employment Performance	Project	NS	0.02	0.38	NS	S	-0.14	-1.56	NS	CF	0.08	1.28	NS
H1-1f	Initial commitment -> Innovation Performance	Project	NS	0.03	0.66	NS	NS	0.13	1.31	NS	NS	0.00	0.02	NS
H1-2a	Discontinuation -> Sales Yield	Project	NS	0.00	0.01	NS	PS	-0.10	-0.41	NS	NS	0.12	1.10	NS
H1-2b	Discontinuation -> Employment Yield	Project	NS	0.01	0.05	NS	PS	-0.11	-0.75	NS	NS	0.08	0.74	NS
H1-2c	Discontinuation -> Innovation Yield	Project	NS	-0.17	-1.56	NS	PS	-0.19	-0.76	NS	NS	0.01	0.11	NS
H1-2d	Discontinuation -> Sales Performance	Project	NS	0.07	0.70	NS	NS	-0.05	-0.29	NS	NS	0.16	1.29	NS
H1-2e	Discontinuation -> Employment Performance	Project	NS	0.03	0.35	NS	NS	-0.13	-1.00	NS	NS	0.09	0.72	NS
H1-2f	Discontinuation -> Innovation Performance	Project	**PS**	**-0.26**	**-2.60*****	**S**	PS	-0.09	-0.59	NS	NS	-0.18	-1.48	NS
H1-3a	Fit -> Sales Yield	Project	NS	-0.10	-0.89	NS	NS	-0.06	-0.37	NS	NS	-0.02	-0.21	NS
H1-3b	Fit-> Employment Yield	Project	NS	-0.13	-1.25	NS	NS	0.03	0.22	NS	NS	-0.07	-0.76	NS
H1-3c	Fit -> Innovation Yield	Project	NS	-0.05	-0.47	NS	NS	-0.18	-0.74	NS	NS	-0.06	-0.70	NS
H1-3d	Fit -> Sales Performance	Project	NS	-0.05	-0.53	NS	NS	-0.05	-0.47	NS	NS	-0.13	-1.16	NS
H1-3e	Fit -> Employment Performance	Project	NS	-0.08	-0.93	NS	NS	-0.01	-0.07	NS	CF	-0.19	-1.87	NS
H1-3f	Fit -> Innovation Performance	Project	NS	-0.05	-0.56	NS	NS	-0.12	-0.83	NS	NS	-0.09	-0.75	NS
H1-4a	Fit -> Sales Yield	Portfolio	**S**	**0.22**	**1.92***	**PS**	NA	-	-	NA	PS	0.15	1.55	NS
H1-4b	Fit-> Employment Yield	Portfolio	**S**	**0.26**	**2.49****	**S**	NA	-	-	NA	NS	0.13	1.28	NS
H1-4c	Fit -> Innovation Yield	Portfolio	NS	0.08	0.78	NS	NA	-	-	NA	NS	0.12	1.39	NS
H1-4d	Fit -> Sales Performance	Portfolio	NS	-0.05	-0.48	NS	NA	-	-	NA	NS	-0.15	-1.28	NS
H1-4e	Fit -> Employment Performance	Portfolio	NS	-0.03	-0.27	NS	NA	-	-	NA	NS	-0.18	-1.46	NS
H1-4f	Fit -> Innovation Performance	Portfolio	NS	0.07	0.70	NS	NA	-	-	NA	NS	0.13	1.06	NS
H1-5a	Sequencing -> Sales Yield	Portfolio	NA	-	-	NA	NA	-	-	NA	**S**	**-0.18**	**-3.37*****	**S**
H1-5b	Sequencing -> Employment Yield	Portfolio	NA	-	-	NA	NA	-	-	NA	**S**	**-0.25**	**-4.94*****	**S**
H1-5c	Sequencing -> Innovation Yield	Portfolio	NA	-	-	NA	NA	-	-	NA	**S**	**-0.14**	**-3.29*****	**S**
H1-5d	Sequencing -> Sales Performance	Portfolio	NA	-	-	NA	NA	-	-	NA	NS	-0.02	-0.44	NS
H1-5e	Sequencing -> Employment Performance	Portfolio	NA	-	-	NA	NA	-	-	NA	NS	-0.03	-0.53	NS
H1-5f	Sequencing -> Innovation Performance	Portfolio	NA	-	-	NA	NA	-	-	NA	NS	-0.01	-0.25	NS
H1-6a	Initial commitment -> Sales Yield	Portfolio	NA	-	-	NA	NA	-	-	NA	**S**	**-0.12**	**-2.00****	**S**
H1-6b	Initial commitment -> Employment Yield	Portfolio	NA	-	-	NA	NA	-	-	NA	**S**	**-0.14**	**-2.21****	**S**
H1-6c	Initial commitment -> Innovation Yield	Portfolio	NA	-	-	NA	NA	-	-	NA	**S**	**-0.10**	**-1.78***	**PS**
H1-6d	Initial commitment -> Sales Performance	Portfolio	NA	-	-	NA	NA	-	-	NA	NS	-0.05	-0.67	NS
H1-6e	Initial commitment -> Employment Performance	Portfolio	NA	-	-	NA	NA	-	-	NA	NS	-0.02	-0.27	NS
H1-6f	Initial commitment -> Innovation Performance	Portfolio	NA	-	-	NA	NA	-	-	NA	NS	-0.03	-0.46	NS

Notes: S – supported, NS – not supported, PS – partially supported, CF – contrary finding, NA – not applicable;
*** p<0.01; ** p<0.05; * p<0.1

Relationship between Signals and Long-term Performance

H3-2: There is a discrepancy between perceived and actual effects of signals on investment yield and firm performance.

Table 9-5 shows whether the factors that were significant predictors of funding allocation outcomes have an effect on investment yield and firm performance. Overall, the results demonstrate that not all important antecedents of performance affect funding allocation outcomes. This suggests that discrepancies exist between perceived and actual effects of firms' legitimacy attributes on performance, thereby supporting Hypothesis 3-2.

Role legitimacy signals are significantly associated with performance outcomes, but their impact is limited at the funding allocation stages. PI's firm tenure is an accurate signal—it negatively affects the magnitude of initial commitment and is also negatively associated with sales and employment outcomes. Although PI's role as a CEO signal decreases the likelihood of funding discontinuation, it negatively affects innovation yield and performance of firms with no prior awards ($t = -2.42$ and $t = -2.09$ at $p<0.05$, respectively). On the other hand, manager's role as a CEO decreases sales and innovation performance of firms with prior awards ($t = -2.55$ and $t = -2.97$ at $p<0.05$, respectively), yet this factor has no impact on funding allocation. This finding is in line with the previous literature confirming that CEO's involvement in functional roles can have differential effects under various circumstances. Science-focused CEOs and management-focused CEOs have different attitudes towards risks of undertaking new investments, with the former being risk-averse and the latter risk-friendly (Kish-Gephart and Campbell 2015). Perhaps, propensity for risk-taking behaviour can explain the negative effect of CEO's involvement on performance. Whereas risk-taking is necessary for innovation, commercialisation and growth require more strategic planning. Therefore, CEO's narrow functionalist perspectives result in underestimation of strategic opportunities, inhibiting innovation in new firms, while CEO's broad functionalist perspectives result in overestimation of strategic opportunities, limiting commercial success and growth in existing firms. Other two indicators of role legitimacy have an impact on performance but are not attended to during Phase I and Phase II evaluation stages of firms' potential. Manager's entrepreneurial experience has a positive albeit weak effect on sales yield and performance of firms with no prior awards ($t = 1.79$ and $t = 1.78$ at $p<0.1$, respectively). PI's entrepreneurial experience, on the other hand, has a strong negative effect on sales and employment performance of firms with prior awards ($t = -3.23$ and $t = -2.78$ at $p<0.01$, respectively). The potential explanation for the findings could be down to the role-experience alignment within the team. The manager with founding experience has a clear commercial task and relevant background to support the execution of commercialisation of projects in inexperienced firms. The PI with an entrepreneurial background, on the other hand, may struggle to balance out personal entrepreneurial aspirations and responsibilities within the team, suggesting that narrow functionality coupled with an inclination towards risk-taking can distort the appreciation of commercial and growth opportunities in more experienced firms. The above findings indicate that the impact of role legitimacy on performance varies depending on the functional background of the TMT member within more and less experienced firms.

Resource legitimacy has a weak signalling power at the funding allocation stages, despite its significant role in explaining performance heterogeneity. PI's professorship is a misleading signal—it is positively perceived at both funding allocation stages, yet it has a negative effect on innovation yield and performance ($t = -2.55$ and $t = -2.97$ at $p<0.05$, respectively). The seemingly counterintuitive finding can be attributed to the role-commitment trade-off that high academic status PIs have to make. Despite the expected full-time involvement of the PIs in the project stipulated by the SBIR programme, it appears that their active academic status may lower their commitment as a practising scientist, which significantly limits the inventive output of the firm. Previous studies also found that spinouts led by the academic inventors tend to underperform (Zerbinati et al. 2012). This can be attributed to the fact that highly-ranked academic entrepreneurs are more likely to stay active in academia, retaining the position of a hybrid entrepreneur (Nicolaou and Souitaris 2016). Toole and Czarnitzki (2009) provide further support for this argument with their conclusion that academic human capital deeply oriented in leading science decreases the innovative performance of the firms.

Three indicators of resource legitimacy—namely, manager's elite education, as well as manager's and PI's MBA degrees—influence performance outcomes, but are not used as signals by investors. Manager's elite education has a positive though weak effect on innovation performance, which indicates that affiliation with high-status and high-quality academic institutions of commercial leaders helps them develop human and social capital necessary to guide innovation efforts in the direction of success. MBA degree is another ambiguous predictor of performance. Manager's MBA degree has a positive and weak effect on sales and employment, but a negative and strong effect on innovation performance of firms with prior awards ($t = -2.24$ at $p<0.05$). This finding supports prior research which found that MBA graduates are on average more strategically and financially aggressive, but engage in less R&D (Bertrand and Schoar 2003). On the other hand, MBA-holding PIs have a weak positive influence on employment yield of firms with no prior awards but a weak negative influence on employment yield of firms with prior awards. Such dual effect can be explained by attitudes towards growth by PIs: commercially minded scientists of inexperienced firms might be more willing to grow the NPD team to explore opportunities, while commercially minded scientists of experienced firms tend to exploit NPD opportunities with in-house human resources.

Three indicators of intellectual legitimacy have an effect on both funding allocation and performance outcomes. Manager's patenting activity has an overall negative albeit weak effect on sales performance (t = -1.75 at p<0.1), and is also negatively perceived by investors, increasing the likelihood of funding discontinuation for firms with prior awards (t = 2.04 at p<0.05), which confirms its accuracy as a signal. This finding complements the argument that TMTs struggle to balance out the role-experience trade-off, as demonstrated by the finding that managers who demonstrate high inventive capacity, lose the focus from their direct commercialisation responsibilities. By the same token, PI's patenting activity has a strong positive effect on innovation yield and performance, particularly of the firms with no prior awards (t = 2.91 and t = 2.79 at p<0.01, respectively). It has also proven to be an accurate signal during Phase I evaluation, with PI's patenting activity being positively associated with the magnitude of initial commitment (t = 2.03 at p<0.05). The clear alignment of PI's narrowly defined functional role within the team coupled with high inventive capacity translates into improved innovation patenting efforts. Finally, PI's publication activity is an important indicator of intellectual legitimacy which has a strong positive impact on innovation yield and performance of firms with prior awards (t = 2.39 and t = 2.42 at p<0.05, respectively), yet diminishes the chances of such firms to attract higher amount of initial funding at Phase I, suggesting that the signal suffers from the misinterpretation bias. Investors associate PI's high publication activity with excessive involvement in academic research. However, as the finding suggests, experienced firms benefit from basic academic research, which stimulates the influx of new knowledge and novel ideas from theoretical developments as well as access to the wider scientific community through co-authorships and conferences. In other words, PI's patenting activity has a positive influence on innovation outcomes of less experienced firms, whereas PI's publishing activity has a positive impact on innovation outcomes of more experienced firms. This suggests the criticality of balancing out exploration-exploitation activities at different stages of the firm's life cycle. The evidence presented here suggests that firms engaged in practical exploitation research enhance innovation performance at earlier stages, while generic exploration research is beneficial for innovation performance at later stages.

The results demonstrate that both indicators of efficacy are strongly associated with performance outcomes, making them the most accurate signals at Phase II evaluation stage. This indicates that investors correctly infer firm's long-term performance from their intermediary performance, supporting the conclusion that what new ventures do is more valuable than what characteristics they possess. Project duration has a negative impact on investment yield, with the strongest effect on innovation yield and performance of firms with no prior awards (t = -3.12 and t = 2.93 at p<0.01, respectively). On the other hand, invention activity has a strong positive impact on sales and employment performance of firms with prior awards (t = 2.38 at p<0.05 and t = 2.97 at p<0.01, respectively). The findings imply that for less experienced firm the ability to keep the experimentation stage short enhances innovation efforts, while for more experienced firms the ability to patent emerging technical knowledge efficiently increases commercial success and growth.

Finally, the results mostly confirm the expectation that capabilities have a significant impact on performance, yet are given little attention at the funding allocation stages due to their low observability. The findings indicate that managerial capability is negatively associated with funding allocation, predominantly at Phase II, which may mean either that the investors intuitively infer managerial capability by observing other indicators of performance, or that strategically-minded managers opt from succeeding through funding stages and seek funding elsewhere. However, in reality, managerial capability has differential effects on long-term outcomes. Overall, firms benefit from the positive influence of managerial capability on innovation yield and performance ($t = 2.10$ at $p<0.05$ and $t = 2.06$ at $p<0.1$, respectively). It also has a strong and positive effect on sales and employment yield and performance of firms with no prior awards. At the same time, managerial capability has a negative effect on sales and employment performance of firms with prior awards ($t = -1.99$ at $p<0.1$ and $t = 2.04$ at $p<0.05$, respectively). R&D and intellectual capabilities also play an important role in explaining performance outcomes, although their signalling effect is insignificant at the funding allocation stages. Effects of capabilities on performance are discussed in more detail in the subsequent section.

In addition to the focal relationships, the results show discrepancies between the perceived and actual effects of controlling factors. Industry volatility has a strong negative impact on sales and employment yield, but does not affect funding allocation outcomes. This finding sheds more light on the execution of ROR logic by government venture funders. As was noted previously, ROR decision-making explicitly accounts for environmental uncertainty when assessing the value of investment options (McGrath 1997), which is not evident in the case of government venture funders. Despite the associated gains from keeping initial commitments low or holding options under high market uncertainty, and exercising options under low market uncertainty (Bowman and Hurry 1993; McGrath 1997), there is no apparent assessment of industry volatility by investors when making initial and subsequent funding decisions. This suggests that investors' understanding of benefits associated with ROR when making investment decisions is limited, which minimises potential gains from the funding programme. On the other hand, the propensity to discontinue funding firms which are headquartered in more innovative states has no real impact on firms' ability to enhance performance. Perhaps, firms continue to suffer from the liability of smallness when approaching finance providers elsewhere in the state. Last but not least, firm age is positively perceived by investors and increases the magnitude of initial funding allocation, but the results demonstrate that in reality firm age has differential effects on various types of performance. Firm age enhances sales and employment yield and performance but reduces innovation yield ($t = -2.52$ at $p<0.05$). This finding implies that older firms are better equipped to commercialise technologies and grow, while younger firms are more creative at generating innovative ideas which can later be patented.

Table 9-5: Comparison of Part II and Part III signalling theory hypotheses testing results

	Part II						Part III																	
	Initial Commitment			Discontinuation			Sales Yield			Employment Yield			Innovation Yield			Sales Performance			Employment Performance			Innovation Performance		
Independent variables:	**Full**	**NA**	**WA**	**Full**	**NA**	**WA**	**Full**	**NA**	**WA**	**Full**	**NA**	**WA**	**Full**	**NA**	**WA**	**Full**	**NA**	**WA**	**Full**	**NA**	**WA**	**Full**	**NA**	**WA**
Role legitimacy																								
Manager CEO																		-/**	-/**		-/**			
PI CEO				-/**	-/*	-/**								-/**									-/**	
PI's firm tenure	-/***	-/*					-/***		-/***	-/***	-/*	-/***				-/**	-/***		-/**	-/**	-/*			
Manager's entrepreneurial experience								+/*									+/*							
PI's entrepreneurial experience																		-/***			-/***			
Resource legitimacy																								
Manager's elite education																						+/*		
Manager's MBA							+/*	+/*		+/*							+/*							-/**
PI's MBA											+/*	-/*												
PI's professorship		+/**				-/*							-/***	-/*								-/***	-/**	
Intellectual legitimacy																								
Manager's patents						+/**										-/*								
PI's patents	+/**		+/*											+/***								+/**	+/***	
PI's publications	-/*		-/**										+/*		+/**							+/**		+/**
Efficacy																								
Project duration				+/**	+/*		-/**			-/**	-/**	-/**	-/**	-/***					-/*				-/***	
Invention activity				-/***		-/**										+/**		+/**	+/**		+/***			
Capabilities																								
R&D capability														+/*								+/*	+/*	+/**
Managerial capability		-/*		+/***		+/*		+/**			+/***		+/**				+/***	-/*		+/***	-/**	+/*		
Intellectual capability								-/*									-/**							
Control variables:																								
Industry volatility							-/***			-/**														
State innovativeness				+/*		+/**																		
Firm age	+/***	+/*						+/**	+/*		+/**	+/**	-/**		-/*	+/***	+/**	+/***	+/**	+/**	+/***			

Notes: Results in the table refer to t-values from corresponding full models.
To preserve space, the table only depicts relationships with significant effects: + sign denotes a positive effect, - sign denotes a negative effect, blank cells depict no effect.
Full – full sample, NA – cluster with no prior awards; WA – cluster with prior awards.
*** p<0.01; ** p<0.05; * p<0.1

Relationship between Interactions of Capabilities and Long-term Performance

H3-3: Interactions of capabilities have both complementarity and substitutions effects on investment yield and long-term firm performance.

Although less observable signals of capabilities were not perceived as important signals, they play a significant role in explaining firm performance outcomes.

The results of Part III analysis show that capabilities and their interactions have differential effects on various types of performance and depending on firms' experience in implementing real options investments. Table 9-6 depicts five prominent patterns of effects of capabilities on investment yield and firm performance of firms with and without prior awards. Recall from the previous chapters that managerial capability refers to manager's efficiency of recognising opportunities and implementing strategic change; intellectual capability refers to PI's academic efficiency which presents a fundamental component of firms' explorative research; R&D capability refers to firm's inventive efficiency and is a reflection of firm's efforts to exploit basic research and apply it to commercial needs. Each pattern of capability configurations is discussed in detail below.

In pattern one, sales and employment outcomes of firms with no prior awards are positively affected by managerial capability but negatively affected by the interaction of R&D and managerial capability. In other words, the direct positive effect of managerial capability is substituted by R&D capability when interacted, meaning that firms' high inventive efficiency distorts managers' ability to recognise new opportunities and implement strategic change. At the same time, for firms with no prior awards, intellectual capability has a negative effect on sales yield and performance ($t = -1.97$ at $p<0.1$ and $t = -2.15$ at $p<0.05$, respectively), while the interaction of R&D and intellectual capability has a negative effect on sales and employment yield ($t = -1.81$ at $p<0.1$ and $t = -2.23$ at $p<0.05$, respectively). Since the proliferation of PI's academic human capital is believed to enhance firms' orientation towards the exploration of new knowledge, it may result in excessive experimentation and pursuit of risky ideas, limiting focus on refinement of existing ones (March 1991). The finding thereby indicates that for the first-time award winning firms, the propensity to engage in novel knowledge-generating research distracts from activities aimed at translating inventions into products which can generate sales. Similarly, the interaction of intellectual and R&D capability can be expressed as the combination of explorative and exploitative research efficiency within the team, or research ambidexterity. As March (1991 p.71) noted in his seminal paper, exploitation encapsulates refinement and execution of existing knowledge, while exploration entails experimentation with newly discovered knowledge. However, simultaneously they also compete for scarce resources, leading to tensions and trade-offs which can have detrimental costs and impose limitations on organisational performance (March 1991). The ambidextrous strategy is particularly difficult to manage for small firms (Ebben and

Johnson 2005). Consistent with the propositions of the extant literature (March 1991; Nerkar 2003), the results demonstrate that knowledge ambidexterity has a negative effect on performance.

In pattern two, sales and employment performance of firms with prior awards is negatively affected by managerial capability ($t = -1.99$ at $p<0.1$ and $t = -2.04$ at $p<0.05$, respectively), but is positively affected by the interaction of R&D and managerial capability ($t = 2.53$ at $p<0.05$ and $t = 2.21$ at $p<0.05$, respectively). Additionally, sales performance of firms with no prior awards is positively associated with the interaction of intellectual and managerial capability ($t = 1.84$ at $p<0.1$). That is, managerial capability can only enhance commercialisation efforts of experienced firms when complemented with firm's inventive capacity or PI's basic theoretical knowledge. This finding broadly supports evidence presented by Voss and Voss (2013) that the interaction of product exploitation and market exploration, as well as product exploration and market exploration, have a positive effect on the performance of SMEs. That is, managerial systems play a profound role is interpreting and integrating individual and technical knowledge dimensions into a cohesive whole (Day 1994).

In pattern three, innovation yield and performance of firms with no prior awards is positively affected by R&D capability ($t = 1.91$ at $p<0.1$ and $t = 1.77$ at $p<0.1$, respectively), and its interaction with managerial capability ($t = 1.94$ at $p<0.1$ and $t = 2.41$ at $p<0.05$, respectively). The interaction of intellectual and managerial capabilities, on the other hand, has a negative effect ($t= -2.12$ at $p<0.05$ and $t = -1.96$ at $p<0.1$, respectively). The positive impact of R&D capability on innovation outcomes is not surprising and supports prior empirical evidence (Dutta et al. 1999). A more poignant implication shown by the results is that for less experienced firms managerial capability is complemented by R&D capability, but substituted by intellectual capability. In other words, to enhance innovative knowledge commercialisation, exploitative research has to be supported by managers' strategic efficiency, thereby allowing new firms to concentrate on extracting maximum potential from existing knowledge assets instead of exploring any new ones.

In pattern four, innovation yield and performance of firms with prior awards are positively affected by the interaction of intellectual and managerial capabilities ($t = 2.19$ and $t = 2.24$ at $p<0.05$, respectively), while R&D capability has a positive impact on innovation yield ($t = 1.98$ at $p<0.05$). Here, in addition to the direct positive effect of R&D efficiency and in sharp contrast to Pattern 3, the combination of PI's academic excellence in generating valuable research ideas and manager's ability to notice strategic opportunities combine in a mutually-enhancing configuration that has a strong positive impact on innovation outcomes. The effect of the latter interaction is consistent with Pattern 2.

Fifth, sales and employment yield of firms with prior awards have no association with any of capabilities or their interactions. This finding implies that capabilities of existing award holders add no value to the investment programme. This is counter to the intention of ROR, which postulates that through a chain of explore-exploit options a firm can learn from prior investments and build a stock of unique resources and capabilities, which can lead to superior performance. The result further emphasises that maximum rents can be appropriated from real options when making small positioning investments that enable firms to explore potential opportunities and develop necessary skills and capabilities for their successful realisation. As the results demonstrate, while established firms continue to benefit from capabilities developed as a result of option-like investments (Pattern 2 and 4), there are no associated returns from funding the same firms to investors.

Table 9-6: Summary of effects of capabilities on performance outcomes

	Pattern 1				Pattern 2		Pattern 3		Pattern 4		Pattern 5	
Capability	**Sales Yield NA**	**Employment Yield NA**	**Sales Performance NA**	**Employment Performance NA**	**Sales Performance WA**	**Employment Performance WA**	**Innovation Yield NA**	**Innovation Performance NA**	**Innovation Yield WA**	**Innovation Performance WA**	**Sales Yield WA**	**Employment Yield WA**
R&D							1.91*	1.77*		1.98**		
Managerial	2.90**	3.47***	3.20***	3.77***	-1.99*	-2.04**						
Intellectual	-1.97*		-2.15**									
R&DXMan	-1.77*	-2.46**	-2.95*	-2.41***	2.53**	2.21**	1.94*	2.41**				
R&DXIntel	-1.81*	-2.23**										
IntelXMan					1.84*		-2.12**	-1.96*	2.19**	2.24**		

Notes: Results in the table refer to t-values from corresponding full models, blank cells depict no effect.
NA – cluster with no prior awards; WA – cluster with prior awards.
*** p<0.01; ** p<0.05; * p<0.1

9.3 Robustness Checks

Consistent with Part I and Part II, robustness checks were also conducted in Part III to determine whether possible heteroscedasticity of data might generate biassed p-values. Appendix 33 reports estimated coefficients and t-values for the full sample SUEST regression model of Part III analysis, Appendix 34 for the cluster with no prior awards and Appendix 35 for the cluster with prior awards.

Robust standard errors produced under SUEST for each regression model have only slightly affected estimates of t-values and corresponding p-values of the full and split sample models. All independent variables established as important explanatory factors of performance outcomes under SUR estimation procedure remained significant. In fact, many effects have lower p-value under SUEST, which further confirms that SUR is a robust technique that produces conservative standard errors. As a result, it can be concluded that the interpretation of results for hypothesis testing is consistent under both modelling techniques.

9.4 Sensitivity Analysis

As in Part I, sensitivity analysis is conducted to examine whether the estimates suffer potential overstatement bias of sales yield and employment yield dependent variables. Appendix 36 shows how estimates change when sales and employment yield is reduced from 100% growth to 10% growth for full and split sample regression models. Additionally, Appendix 37 presents t-values based on robust standard errors for equations with 10% growth sales and employment yield as dependent variables.

Overall, none of the hypothesised relationships significantly changed their effects. The differences in estimates produced by the base model and the adjusted model are minute, which signifies that the findings are not sensitive to potential variations in the dependent variables, so hypotheses testing holds true.

9.5 Summary

The contribution of Part III analysis is threefold. First, the results confirm that prescriptions of ROR logic hold in the presence of other firm-level factors, suggesting that real options theory applies to practical organisational settings.

Second, there is an element of mismatch between the expected and actual impact of signalling characteristics on performance. The results indicate that effects of characteristics are not universal across firms with different levels of experience in implementing real options. Role-experience and role-commitment alignments within the team have important implications for performance. As Toole and Czarnitzki (2009 p.113) argued, the contribution of academic entrepreneurs is conditional upon the "match" between their specialised human capital and specific task within the firm. The authors stated that the scientifically-oriented human capital enhances research performance of firms, whilst commercially-oriented human capital enhances their inventive performance.

Finally, the findings emphasise that depending on whether or not the firms have received funding before, they will require distinct combinations of capabilities to achieve different types of performance. The orientation of human capital toward scientific or commercial opportunities can influence firms' growth strategies (Toole and Czarnitzki 2009 p.113). Less experienced firms necessitate a relatively straightforward skillset: managerial capability is critical to stimulate sales and employment creation and also to enhance the direct positive effect of R&D capability on innovation outcomes. At the same time, less experienced firms should refrain from engaging in explorative and ambidextrous research following their opening of an option. More experienced firms, on the other hand, are faced with a more complex task: they need a combination of R&D and managerial capability to enhance sales and employment creation, and the combination of intellectual and managerial capability to enhance innovation performance. On its own, though, managerial capability reduces commercial outputs. That is, generation of innovation is made possible by PI's search for novel ideas and manager's ability to recognise their strategic potential, which should not, however, distract managers from the concurrent exploitation of firms' existing inventions for commercial potential. By balancing a chain of simultaneous research activities, strategically adept managers of experienced ventures can create the virtuous cycle of value maximisation.

Overall, the results demonstrate that firms' age and experience in managing real options matter a great deal. Thus, the goal of the government programme to meet all three objectives simultaneously might be unrealistic given the unique sets of resources and capabilities that each performance outcome necessitates. Unless the funds are allocated strategically, for instance, with grants to younger firms being specifically directed to innovation and grants to older firms being specifically directed to commercialisation, the value offered by the programme gets eroded.

Chapter 10 - Conclusions, Implications, Limitations and Future Research Directions

10.1 Introduction

The role of VC in fostering entrepreneurship has been recognised at the academic and policy levels, and research found evidence of its positive impact on innovation, employment creation and economic growth (Samila and Sorenson 2011; Dutta and Folta 2016). The study makes an addition to this body of work by narrowing down the VC context to a specific type of investor, namely government. Governmental programmes are designed to financially support strategically important projects, such as R&D. Governmental subsidies for innovation and entrepreneurship activities have been extensively scrutinised in the literature and yet little consensus exists regarding the efficiency of such initiatives (Brander et al. 2014; Grilli and Murtinu 2014; Bertoni and Tykvova 2015). Empirical evidence from the U.S. and Europe indicated that more research is needed on assessing the design of public venture capital programmes in order to understand whether such initiatives could benefit from more structural changes and improved selection processes (Lerner 1999; Munari and Toschi 2015; Alperovych et al. 2015).

To address these issues, the primary research objective was to move away from the prevailing question in the extant literature on whether the provision of public venture capital helps SMEs innovate and grow, and instead to explore how and when investors and participants benefit most from the implementation of public financing programmes. This study has sought to assess the private and social impacts of the public programme by integrating investor's and investee's perspectives of target outcomes, which relate to sales, employment and innovation performance.

Defined by a discretely staged and sequential financing structure (Sahlman 1990; Gompers 1995; Trigeorgis 1996) and by conditions of high uncertainty (Amit et al. 1998), venture capital presents a distinctive setting for testing propositions postulated by real options theory and allows gaining insights into the behavioural aspects of the decision-making process of resource allocations. On the one hand, the study utilised real options reasoning to understand the strategies of financial resource allocations; on the other hand, it attended to signalling theory and attention-based view to explore the process of resource allocation decision-making.

The study provides evidence from a novel multi-source data set on the antecedents and consequences of resource allocation outcomes of government venture funding. In broader terms, the study adds to the literature on real options theory and financing of innovation and SMEs, and more specifically, to the area of resource allocations and strategic management of innovation investment portfolios. Finally, by testing hypotheses in the context of the public capital market, the study adds to the literature on government venture funding and public subsidies.

This final chapter presents the SWOT aspects of the entire study: strengths are presented as a set of summary insights and concluding implications for theory and practice; weaknesses and threats are related to the issues of external and internal validity of the findings; finally, a number of opportunities are expressed as directions for future research.

10.2 Conclusions

Summary of the Main Insights

Contribution to the Understanding of Resource Allocation Strategies under Real Options Reasoning

The results presented in this study extend the empirical inquiry into the relationship between the strategic resource allocation decisions under ROR and performance, and confirm their direct positive impact. These results hold in the presence of firm-specific factors, indicating that ROR theory is applicable to practical organisational settings. As such, the study contributes to the rather small body of work on resource allocation strategies which has only started to emerge recently (Klingebiel and Rammer 2014; Klingebiel and Adner 2015).

First, the study found that the magnitude of initial commitment and high rate of sequencing have a diminishing effect on investment yield. Second, consistent matching of funding decisions across the entire portfolio of options promises positive returns from the investment process. In particular, the results demonstrate that the continuation decision should be informed by the magnitude of initial commitment. Finally, new options are subadditive to the existing portfolio and do not enhance investment yield, suggesting that, contrary to expectations, the firms that receive a higher number of subsidies do not capture more benefits from the support of their research. Generally, ROR elements have a strong significant effect on funders' target outcomes but not on project owners' or project managers' target outcomes, corroborating the role of ROR as an investment tool to support optimal decision-making.

For the most part, the magnitude and the increased number of awards seem to have a cannibalisation effect on firms' performance which can be a result of one or a combination of the following possible explanations. First, as nascent high-tech firms typically comprise a small research team led by a principal scientist and a manager, multiple projects in the portfolio might compete for scarce human capital resources and divert the attention of TMT from commercialising research towards developing research projects (Lerner 1999). On the other hand, 'scaling up' the project team at the early stages by hiring more personnel may not be a feasible objective as the project still has uncertain prospects for success (Lerner 1999). At the same time, entrepreneurs may exhibit opportunistic behaviour and seek larger or more grants to increase salaries of knowledge workers, which is unlikely to be reflected in innovation efforts. Finally, the number of awards is not expected to enhance the certification effect (Lerner 1999). Therefore, small initial commitments and limited follow-on funding would be most beneficial in stimulating innovation activities (Goolsbee 1998).

By adopting a multi-level multi-stakeholder approach, the analysis revealed differential effects of ROR resource allocation elements on (i) various types of performance, i.e. sales, employment versus innovation; (ii) investors versus investees, (iii) first-time award holders versus multiple-award holders. These insights delineate the boundary conditions in the context of government venture funding.

Contribution to the Understanding of Investment Decision-Making Practice

The use of signalling theory pointed out the characteristics of candidates that make investors deviate from the optimally small initial commitments and affect the likelihood of the option to discontinue funding.

Specifically, the study found that R&D options of multiple award holders attract higher initial commitments when their top scientists have proven technical expertise, expressed as technical experience and patenting record. On the other hand, for first-time award holders top scientists with a high academic status (PI's professorship) and fewer years in the firm increases the initial funding commitment. Taken together, for firms with prior awards, investors prioritise intellectual and role legitimacy of the TMT, whereas for firms with no prior awards, resource legitimacy of the TMT is key.

The results shed light on later-stage funding allocation outcomes by showing that the discontinuation of the option is less likely when the CEO participates in technical roles. The likelihood of discontinuation is also lower when first-time award holders can achieve shorter experimentation time, whereas multiple award holders can increase inventive output.

In addition to signalling theory, the attention-based view provided insights into the types of distortions and deviations inherent in the investment decision-making process. Kogut and Kulatilaka (1994a) noted that organisational heuristics tend to be driven by short-termism, causing strategic myopia. The study finds support for this notion by showing that project appeal characteristics of multiple-award holders such as narrow project scope and cancer biology research override legitimacy characteristics in terms of weight, suggesting that allocation decisions are informed by the government's research needs and priorities more than the firms' potential to carry out research. Prior funding decisions have a strong attention-distorting effect on current funding allocation outcomes revealing the presence of decision-making inertia. These findings add to the literature on information processing and suggest that investment decision-making is often informed by intuitive heuristics, which result in evaluation bias and disagreement between the pre-selected and actual selection criteria (Howell and Jaegle 1997).

Overall, the results depict that less observable signals have no effect on funding allocation decisions, conforming with the primary tenets of signalling theory and the ABV that only readily observable signals can get noticed and reacted upon. The findings show that more relevant categories of characteristics receive higher weights in the decision-making process, followed by salient and only then by observable categories.

Contribution to the Understanding of Investment Decision-Making Accuracy

The results indicate that there is a discrepancy between the expected and actual impact of characteristics used as signals on long-term performance, suggesting that decision-making is prone to inefficiency.

The findings indicate that the use of standardised evaluation criteria prevents decision-makers from distilling high-profile candidates from a pool of applicants. In particular, the results demonstrate that firms require different combinations of skills and capabilities depending on their experience in managing options and the type of target outcome. Based on the results of Part III analysis, Table 10-1 presents 'ideal' configurations of characteristics associated with high-profile candidates. Generally speaking, to achieve performance improvements, firms with no prior awards need to focus on developing the commercial orientation, whereas firms with prior awards should prioritise scientific orientation.

Table 10-1: Characteristics of an 'ideal' high-profile candidate

Target outcome	Firms with no prior awards			Firms with prior awards		
	Characteristics	**Emphasis on**	**Orientation**	**Characteristics**	**Emphasis on**	**Orientation**
Sales yield	High manager's entrepreneurial experience Manager's MBA Managerial capability High firm's age	Manager's role-resource commercial alignment	Commercial	Low PI's firm tenure High firm's age	PI's technical skills	Scientific
Employment yield	Low PI's firm tenure PI's MBA Low project duration Managerial capability High firm's age	TMT's commercial skills	Commercial	Low PI's firm tenure PI's non-MBA Low project duration High firm's age	PI's technical skills	Scientific
Innovation yield	Manager CEO PI non-professor PI's patents Low project duration R&D capability R&D X Managerial capability	PI's exploitative research and manager's commercial skills	Commercial & scientific exploitative	PI's publications Intellectual X Managerial capability	PI's explorative research skills	Scientific explorative
Sales performance	High manager's entrepreneurial experience Low PI's firm tenure Manager's MBA Managerial capability High firm's age	Manager's role-resource commercial alignment	Commercial	PI CEO Low PI's entrepreneurial experience High inventive activity High firm's age R&D X Managerial capability	PI's role-experience functional alignment	Scientific exploitative
Employment performance	Low PI's firm tenure Managerial capability High firm's age	Manager's commercial skills	Commercial	PI CEO Low PI's firm tenure Low PI's entrepreneurial experience High inventive activity High firm's age R&D X Managerial capability	PI's role-experience functional alignment	Scientific exploitative
Innovation performance	Manager CEO PI non-professor PI's patents Low project duration R&D capability R&D X Managerial capability	TMT's technical and commercial skills	Commercial & scientific exploitative	Manager non-MBA PI's publications R&D capability Intellectual X Managerial capability	PI's explorative research skills	Scientific ambidextrous

10.3 Implications

Theoretical Implications

One of the primary implications derived from the current analysis is that ROR theory has important empirical validity, and its understanding can be enhanced by integrating aspects from behavioural theories.

The findings presented here parallel the prior results that there exists a weak and approximate correspondence between decision-makers' intuition and real options theory. The discrepancy between the actual and prescribed investment behaviour has been uncovered in the extant studies (e.g. Busby and Pitts 1997; Triantis 2005; Howell and Jaegle 1997) and described as an *"intriguing paradox"* (Miller and Shapira 2004 p.281). At the heart of this paradox is the compelling evidence that investment decisions reflect some primary elements of real options logic, yet such decisions are made intuitively rather than rationally.

Even in the presence of apparent biases and inefficiencies, decision-makers can roughly conform to the normative tenets of real options theory leading to *"directionally correct"* investment patterns (Miller and Shapira 2004 p.281) when employing qualitative assessments to assist in the decision-making process (Miller and Waller 2003).

The results point out that the extent to which decision-makers follow the real options reasoning investment logic to allocate financial resources to projects has significant repercussions for the process of value creation. The options approach helps investors contain risk by strategically managing financial resource allocations, leading to superior long-term returns on investments, but it does not necessarily enhance firms' performance. This suggests the role of ROR as a decision-making tool, rather than a core ingredient for sustained competitive advantage.

The applicability of real options theory in practice may be limited by agency problems, when, for instance, personal goals of decision-makers conflict with the organisational goals of value maximisation, or when optimal rules and prescriptions are ignored (Trigeorgis 2005). The study documents that there exists a systematic tendency towards overinvestment, both at the initial option opening stage and subsequent exercising stage. Poor investment choices, however, trigger a chain of detrimental effects. Systematic overinvestment puts constraints on the overall budget, resulting in the reduced quota of awards which may untimely rule out potentially lucrative ventures. Generally speaking, the tendency for overinvestment increases the opportunity cost of competing investments as more potentially promising entrepreneurial opportunities are foregone in favour of a smaller number of more expensive options.

The promise offered by real options reasoning heuristics can only be fulfilled if organisations have explicit structures and processes in place that assist with real options decision making, and avoid tendencies to overinvest by striking too many options or to underinvest by failing to strike promising options (Coff and Laverty 2007). Rational matching of options offers a way to limit the propensity for overinvestment. One of the advantages of matching decisions is expressed in its mechanism to confine the tendency towards escalated commitment. Subsequently, consistent matching of funding decisions can be utilised as a simple rule of thumb to enhance the process of value creation, and even substitute explicit risk assessment techniques to quantify the value of options and embedded uncertainty.

Managerial Implications

The results can be used to inform innovative SMEs operating in high-tech sectors, including pharmaceuticals and biotech, applying for government funding. The findings outline which inherent qualities and characteristics entrepreneurs need to emphasise in the application process to increase their chances of receiving R&D grants.

The assessment of unique resources and capabilities in order to differentiate between high-quality and low-quality candidates is complex. It seems that investors base their initial decision on the static indicators of TMT's legitimacy, but attend to flow signals to derive new ventures' operational performance. Broadly speaking, to reveal TMT's integral abilities, first-time award holders need to strategically signal resource legitimacy, whilst multiple-award holders need to clearly signal intellectual and role legitimacy. The results demonstrate that while static signals of TMT background help resolve a portion of uncertainty at early funding stages, to prove the suitability for later-stage funding, nascent ventures need to demonstrate their operational legitimacy. This agrees with the notion that what entrepreneurs do is more important than who they are (Tornikoski and Newbert 2007). These findings provide a clear indication to entrepreneurs that while their background and experience characteristics (e.g. PI's low tenure and PI's patents) are necessary indicators of confirming legitimacy that allows gaining traction in the market for early-stage funding, static characteristics of the TMT alone are insufficient for receiving continuous financial support. The strong relationship between efficacy signals and the likelihood of receiving late-stage awards indicates that acceptance of nascent entrepreneurs by external investors is a function of their intermittent performance more than their cumulative human capital. The results suggest that entrepreneurs need to concentrate on proactively engaging in specific behaviours, namely shorter experimentation and higher inventive activity in an effort to gain operational legitimacy in the eyes of external funding providers.

Another notable finding is that the readability of project narratives has no impact on funding allocation decisions. This is in line with prior studies that asserted that some information contained in business plans weakly affects VC funding decisions (e.g. Kirsch et al. 2009). Perhaps, due to the intrinsic complexity associated with projects related to cancer research, the effective communication of intricate information is not viewed as a relevant cue by decision-makers to assess the abilities of the applicants.

Additionally, the SMEs should bear in mind that the funding allocation process is hugely driven by the government's agenda for scientific R&D. As a result, to align the application with government's research needs and priorities, the entrepreneurs might benefit from referring to the solicitation listing that outlines calls for proposals and funding opportunities.

Finally, the summary results presented in Table 10-1 show that contingent upon their experience in the venture funding programme, the SMEs require specific skills and capabilities to achieve different types of target outcomes. The findings indicate that first-time funding holders should concentrate on developing a commercially-oriented TMT in order to develop their research ideas to the stage where they become ready for commercialisation. On the other hand, holders of multiple funding awards require TMTs with a continuous focus on the scientific orientation and need to be able to balance competing exploration and exploitation research activities.

Implications for Public Policy Makers

As was noted in the introduction chapter, governments of the major OECD economies have been increasing the amount of public financial resources in support of R&D of small innovative ventures. As a consequence of this trend, a significant amount of effort has been devoted in academic and public policy domains to understand the role of the provision of public support for R&D projects in helping small financially constrained firms grow and in fostering innovation in high-tech SME sectors.

The results of the present study point out a number of implications for public policy makers related to structural and behavioural issues which cause deficiencies in the evaluation process. Overall, the use of taxpayers' money is inefficient, which implies that these programmes warrant restructuring or at least reassessment.

Rigid Evaluation

The results of the analysis summarised in Table 10-1 imply that government venture funders cannot 'kill two birds with one stone' by using standardised evaluation methods for both experienced and inexperienced participants. This is because nascent ventures necessitate different configurations of skills and capabilities to succeed. Therefore, the programme would benefit from a more fine-grained approach that takes account of different backgrounds of entrepreneurial firms during the evaluation process.

Inaccurate Evaluation

The analysis revealed that deviations exist in decision-making from prescriptions of ROR indicating that investment patterns of government venture capitalists only partially reflect real options reasoning in practice. The finding that consistent implementation of ROR in organisational settings offers significant benefits, therefore, reinforces the need for training of government venture capitalists in implementing allocation financial resources in line with the real options approach (Howell and Jaegle 1997).

Some heuristics were found to be deficient, while a number of evaluation criteria appeared to be utilised inaccurately. The latter finding indicates that investors may have limited mechanisms in place to accurately evaluate the value of R&D projects and, in addition to tailored training, may benefit from advanced computer-aided analytical tools, which is consistent with recommendations by other scholars (e.g. Miller and Shapira 2004). Developing selection criteria based on factors that predict venture's success would help decision-makers differentiate between high-achievers and under-achievers (Lerner 2002). Therefore, the evaluation bias could be further minimised by explicitly taking into account the factors that are related to the achievement of desired outcomes by referring to Table 10-1. Broadly speaking, the results indicate that commercially-oriented TMTs of first-time award holders and scientifically-oriented TMTs of multiple-time award holders have higher chances for success and hence such indicators can be used by decision-makers as reliable heuristics during the selection and evaluation process.

Inefficient Monitoring

As was noted in the prior literature, government VC do not scrutinise the track record of applicants to the same degree as private VC. Sceptics pointed out that some government-funded innovative firms *"have found a profitable niche with little incentive to venture into commercial markets"* (Feldman and Kelley 2006). Taking into account the past performance of firms that have previously received government funding is particularly critical as it makes firms accountable for their progress (Lerner 2002). Low track record from prior grants is an indication that future progress is unlikely to be satisfactory. As such, the structure of the programme could benefit from the explicit, integrated and compulsory ex-post assessment of the performance of applicants in relation to each grant that they have been awarded. Overall, the process should strictly monitor how much funding the firms have previously received.

In fact, the programme could be significantly improved if government venture funders got actively involved in the monitoring and controlling of investees in a way similar to private venture capitalists. For example, the critical need of first-time award holders to have a developed managerial skillset suggests that government venture capitalists could assist entrepreneurial teams lacking commercial experience in appointing professional managers specialising in running small firms (Lerner 2002).

Inefficient Structure

The results presented here support the studies that came to a conclusion that the design and structure of public programmes are crucially important (Feldman and Kelley 2006), and yet they are currently subjected to failures and require re-examination (Alperovych et al. 2015).

Specifically, the study indicates that the magnitude and high number of later stage grants do not increase the productivity of ventures necessary for subsequent commercialisation and growth, thereby decreasing investment yield. Therefore, the value from the investment process can be extracted when positioning trial commitments are small, and follow-up funds are allocated in a selective and disciplined manner. Allocation of more modest governmental awards could have a positive effect on the growth of small firms through the certification mechanism (Lerner 1999) or the prototyping channel (Howell 2015).

To sum up, this study's notable implications for policy makers suggest that government venture programmes like the SBIR should be structured in such a way that (i) early-stage awards are low-cost and offered to a larger number of participants, and (ii) later-stage awards are allocated to participants with no other options in the portfolio. The primary idea behind the proposition is that first-time participants of the programme should be given priority over multiple-award holders—the conclusion completely supported by a recent study of Howell (2015).

10.4 Limitations & Future Research Directions

Having discussed the main findings and their primary implications for theory, practice and public policy, several words of caution are offered in relation to the data and analysis performed and how the findings could be taken further.

Theoretical Issues

Causal Direction of Relationships

The first word of caution relates to the fact that there might be potential ambiguity about the direction between the hypothesised cause and effect constructs. There is evidence of the selection bias inherent in the resource allocation process as a result of government venture funders' preference of certain types of projects or structural inefficiencies of the programme. This raises an issue of potentially reversed causality, whereby it remains unclear whether government subsidies help ventures improve commercialisation and growth outcomes, or whether the ventures are awarded grants because they have all the necessary prerequisites to achieve such outcomes at the time of application.

While a thorough endogeneity analysis did not uncover any problems, the issue is still of theoretical importance. Care was taken to select accurate instrumental variables, yet it is still difficult to ascertain that all potentially relevant instruments were considered. The options for instruments were naturally limited by the data availability. Therefore, future research should continue to make an effort towards understanding the questions related to causal directions of relationships by selecting robust instruments and statistical modelling techniques.

Potential Contamination of Theoretical Assumptions

As apparent from Part II analysis, models built upon propositions of signalling theory have a limited explanatory power.

One potential explanation can be that investors follow ROR inconsistently, as a result of which Part II dependent variables—initial commitment and discontinuation—might suffer contamination from behavioural intentions of investors. It currently remains unclear to what extent government venture funders understand the benefits of ROR and explicitly follow the logic. That is, although ROR logic prescribes that rents can be maximised when initial funding commitments are low, significant variability can be observed in the magnitude of initial commitment. This makes it difficult to demarcate government venture funder's logical and perceptual decision-making rationale. In other words, if investors deliberately allocate high initial commitment and continue funding high-potential firms, it suggests firms' legitimacy attributes drive their propensity towards perceptual decision-making. On the other hand, under the ROR investment logic, investors are aware that high-potential firms can extract as much value from low initial commitment and timely discontinuation of funding. Therefore, a better understanding of intentions underpinning decision-making process of government venture funders could help improve the model predicting funding allocation outcomes. In particular, it could shed light on the funding allocation outcomes of the firms with no prior awards, which are currently weakly explained by the conceptual model developed in this project. Perhaps, either a different theoretical lens or more fine-grained analyses are needed to understand which factors explain the phenomenon.

The second issue worth noting relates to the potential contamination of Phase II funding outcome, conceptualised as discontinuation. As Howell (2015) indicated, some firms opt not to apply for Phase II. Given that the current study had no data on whether the ventures received any funding from other sources (internal or external) preceding, during or after the participation in the programme, it was difficult to establish to what extent potential 'opting out' by the participants is of concern. Future research could address this issue.

In the present study, Phase II decision is treated as an outcome and is based on the observable fact that some Phase I projects received Phase II funding, while others did not. However, the model does not capture the factors explaining this outcome. One of the explanatory factors that has not been included in the model is the variable, perhaps a dummy, distinguishing the cases when Phase I awardees applied for Phase II and did or did not receive funding, versus the cases when Phase I awardees did not apply for Phase II. Then, it could be further investigated whether at this stage nascent firms chose to apply for any other type of external support such as private venture funding, and, more importantly, whether they received such support. This would provide evidence of the certification effect of grants, or lack thereof.

As was mentioned in the methodology chapter, the study covers Phase I and Phase II awards. There is also a stipulated, albeit unfunded under the initiative, Phase III leading to commercialisation, which the participants are strongly encouraged to undertake. Perhaps, future research could address this potential avenue and explore (i) whether firms undertake the formal Phase III, (ii) how Phase III is structured and funded, and also (iii) what are the outcomes of Phase III and how it fits with Phase I and Phase II funding.

Categorisation of Signal Attributes

The present study distinguishes between more and less observable signal categories, which, some might argue is a theoretically crude demarcation. For a signal to be considered as a signal, it needs to be readily observable to the receiver. This condition is explicitly taken into account: the study distinguishes between the signals that can be easily observed (e.g. all information that is included in the application form in its raw format) versus the signals that require time and effort to be observed (e.g. capabilities)[37]. While the categorisation of signals on the observability spectrum is deliberate and plausible in the present context, future studies could address to what extent this categorisation is applicable to other settings. The understanding of normative and descriptive tenets of signalling theory could also be enriched by exploring possible interaction effects among signals. For example, it could be investigated whether less observable signals need to interact with more observable signals to trigger the response of the receiver of the signal.

Methodological Issues

Sample

The classical concerns related to the sampling apply. First, the sample is limited to the SBIR programme funded by the National Cancer Institute (NCI) of the National Institute of Health (NIH) in the U.S., making the findings programme-, agency- and country-specific. Currently, it remains unclear to what extent these findings are generalisable to the entire SBIR programme, and similar initiatives in other countries. Second, the adopted research design is longitudinal yet truncated. It means that some grants may have had an effect beyond the period studied here. Third, the sample is randomly generated. However, much richer understanding of the functioning of the programme would be enabled by taking the entire population. It would allow investigating the effect of each individual grant on performance outcomes. To address these limitations, future research could attempt to replicate the findings of the present study in other empirical settings and using more longitudinal designs.

[37] Prior literature has also distinguished between signals along its cost axis, ranging from expensive to cheap signals.

Selection, Operationalisation and Measurement of Constructs

It is well established that the estimation and modelling robustness is contingent upon the selection and validity of measurement instruments. Two issues are believed to be worthy of discussion here.

Capabilities were measured using the input-output model based on the stochastic frontier estimation. In particular, two measures are novel and have been presented for the first time. Similar to the identification of instrumental variables for the endogeneity analysis, the selection of valid outputs and inputs for the stochastic frontier estimation is challenging. Multiple conceptualisations of capabilities exist in the extant literature, and each has theoretical validity. While it is believed that the conceptualisations of selected capabilities closely reflect the theoretical underpinnings, there remains an untested question related to the extent that chosen inputs and outputs are appropriate and extensive. For example, the choice was limited to the data available from the secondary sources. Future research could dedicate empirical effort to developing alternative measures using the same analogy, or propose new alternatives, even using other methods, such as Bayesian analysis.

Another limitation relates to the fact that the measurement of the attractiveness of technology was outside the scope of the current study. One way future research could approach the development of the 'technology attractiveness' measure is by creating a rating scheme in conjunction with industry experts and then applying it empirically to assess the narratives of projects submitted as part of the application pack. Whereas the first, scale development, step is more complex and time-consuming, the second, implementation, step could be facilitated by using methods such as the computed-aided textual analysis.

Additionally, access to internal data on applications would offer a useful indication of the overall quality of candidates and develop a more accurate understanding of what makes some applications more attractive in comparison to others. While it was beyond the scope of the present study to negotiate such access, perhaps future research could find the means to overcome this obstacle.

Imputation Algorithm

The final point that needs mentioning concerns the choice of the imputation algorithm. Although at the time of assessment Amelia imputation algorithm was deemed the most appropriate, it later became apparent that there are more robust imputation methods available (e.g. 'mice' algorithm or Bayesian methods). It has been recently recognised that there is a dearth of practical literature on the imputation methodology, and currently, work is being undertaken[38] to advise social

[38] By the academic team of Professor Donald B. Rubin in Harvard University.

scientists on the methods, tools and techniques that need to be considered to carry out imputation efficiently. Future research should take the results derived from the imputed datasets with caution and be aware of the alternatives.

10.5 Concluding Remarks

The study examined the antecedents and outcomes of investment decisions in the government venture capital setting over a seven-year period. On the one hand, the analysis offers new insights into the normative aspects of real options theory by testing whether theoretical propositions have empirical value in the context of public venture capital. On the other hand, by studying public venture capitalists' sense-making, the study contributes to the understanding of the descriptive tenets of ROR theory.

On the normative side, the research project explored to what extent the implementation of investment resource allocation strategies in line with prescriptions of real options logic offers performance advantages. The findings support the premise that public venture capital decision-makers intuitively utilise real options reasoning, as demonstrated by the fact that consistent matching of funding decisions occurs in only around half the cases, and industry volatility does not affect outcomes of resource allocation decisions the way it is asserted in normative real options models. The results imply that the consistent implementation of the options approach offers significant benefits to developing the optimal investment procedures in the strategy field.

On the descriptive side, the study investigated the patterns of strategic funding decisions that are reflected in the observed investment behaviour. First, the study draws on the multilevel model to derive the factors that affect funding allocation decisions. By integrating individual-, project- and firm-level factors in a coherent model it provides a deeper understanding of the distinct and joint effects of categories of signals. Second, the study documents the presence of distortions in the investment decisions–specific categories of signals that derail decision-makers' attention from the pre-selected evaluation criteria. Therefore, it adds to the body of literature reporting that evaluation biases occur in a systematic fashion.

The present study offers a set of propositions that may help increase the effectiveness of sequential decision-making. To the best of our knowledge, this is one of the few studies to empirically test the premises of logical financial allocations under the options approach so extensively.

References

Aabo, T. and Simkins, B.J. 2005. Interaction between real options and financial hedging: fact or fiction in managerial decision-making. *Review of Financial Economics* 14(3–4), pp. 353–369.

Abayomi, K. et al. 2008. Diagnostics for multivariate imputations. *Journal of the Royal Statistical Society. Series C: Applied Statistics* 57(3), pp. 273–291.

Aboulnasr, K. et al. 2008. Competitive response to radical product innovations. *Journal of Marketing* 72(May), pp. 94–110.

Acs, Z.J. et al. 1992. Real effects of academic research: comment. *American Economic Review* 82(1), pp. 363–367.

Acs, Z.J. and Armington, C. 2004. Employment growth and entrepreneurial activity in cities. *Regional Studies* 38(November), pp. 911–927.

Acs, Z.J. and Audretsch, D.B. 1988. Innovation in large and small firms: an empirical analysis. *American Economic Review* 78(4), pp. 678–690.

Acs, Z.J. and Varga, A. 2005. Entrepreneurship, agglomeration and technological change. *Small Business Economics* 24(3), pp. 323–334.

Admati, A. and Pfleiderer, P. 1994. Robust financial contracting and the role of venture capitalists. *Journal of Finance* 49(2), pp. 371–403.

Adner, R. 2007. Real options and resource reallocation processes. *Advances in Strategic Management* 24, pp. 363–372.

Adner, R. and Helfat, C.E. 2003. Corporate effects and dynamic managerial capabilities. *Strategic Management Journal* 24(10), pp. 1011–1025.

Adner, R. and Levinthal, D.A. 2004a. Real options and real tradeoffs. *Academy of Management Review* 29(1), pp. 120–126.

Adner, R. and Levinthal, D.A. 2004b. What is not a real option: considering boundaries for the application of real options to business strategy. *Academy of Management Review* 29(1), pp. 74–85.

Aerts, K. and Schmidt, T. 2008. Two for the price of one? Additionality effects of R&D subsidies: a comparison between Flanders and Germany. *Research Policy* 37(5), pp. 806–822.

Agarwal, R. and Shah, S.K. 2014. Knowledge sources of entrepreneurship: firm formation by academic, user and employee innovators. *Research Policy* 43(7), pp. 1109–1133.

Ahuja, G. et al. 2013. The second face of appropriability: generative appropriability and its determinants. *Academy of Management Review* 38(2), pp. 248–269.

Aigner, D. et al. 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6(1), pp. 21–37.

Akcigit, U. and Kerr, W.R. 2015. *Growth through heterogeneous innovations*. NBER Working Paper No. 16443.

Alessandri, T.M. et al. 2007. Strategic implications of valuation: evidence from valuing growth options. *Advances in Strategic Management* 24, pp. 459–484.

Al-Laham, A. and Souitaris, V. 2008. Network embeddedness and new-venture internationalization: analyzing international linkages in the German biotech industry. *Journal of Business Venturing* 23(5), pp. 567–586.

Allison, P.D. 1999. *Multiple regression: a primer*. Thousand Oaks, CA: Pine Forge Press.

Almazan, A. et al. 2008. Attracting attention: cheap managerial talk and costly market monitoring. *Journal of Finance* 63(3), pp. 1399–1436.

Almeida, P. and Kogut, B. 1997. The exploration of technological diversity and the geographic localization of innovation. *Small Business Economics* 9(1), pp. 21–31.

Almeida, P. and Kogut, B. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management Science* 45(7), pp. 905–917.

Alperovych, Y. et al. 2015. How does governmental versus private venture capital backing affect a firm's efficiency? Evidence from Belgium. *Journal of Business Venturing* 30(4), pp. 508–525.

Alperovych, Y. and Hübner, G. 2013. Incremental impact of venture capital financing. *Small Business Economics* 41(3), pp. 651–666.

Alvesson, M. and Spicer, A. 2012. A stupidity-based theory of organizations. *Journal of Management Studies* 49(7), pp. 1194–1220.

Amit, R. et al. 1998. Why do venture capital firms exist? Theory and Canadian evidence. *Journal of Business Venturing* 13(6), pp. 441–466.

Amit, R. and Schoemaker, P.J.H. 1993. Strategic assets and organisational rent. *Strategic Management Journal* 14(1), pp. 33–46.

Anderson, T.J. 2000. Real options analysis in strategic decision making: an applied approach in a dual options framework. *Journal of Applied Management Studies* 9(2), pp. 235–255.

Andries, P. and Faems, D. 2013. Patenting activities and firm performance: does firm size matter? *Journal of Product Innovation Management* 30(6), pp. 1089–1098.

Arora, A. and Nandkumar, A. 2012. Insecure advantage? Markets for technology and the value of resources for entrepreneurial ventures. *Strategic Management Journal* 33(3), pp. 231–251.

Arthur, W.B. 1989. Competing technologies, increasing returns, and lock-in by historical events. *Economic Journal* 99(394), pp. 116–131.

Aschhoff, B. and Sofka, W. 2009. Innovation on demand—can public procurement drive market success of innovations? *Research Policy* 38, pp. 1235–1247.

Atanassov, J. et al. 2007. *Finance and innovation: the case of publicly traded firms*. Working Paper. University of Michigan, Ann Arbor.

Atanassov, J. 2016. Arm's length financing and innovation: evidence from publicly traded firms. *Management Science* 62(1), pp. 128–155.

Audretsch, D.B., Link, A.N., et al. 2002. Public/private technology partnerships: evaluating SBIR-supported research. *Research Policy* 31, pp. 145–158.

Audretsch, D.B., Weigand, J., et al. 2002. The impact of the SBIR on creating entrepreneurial behavior. *Economic Development Quarterly* 16(1), pp. 32–38.

Audretsch, D.B. 2003. Standing on the shoulders of midgets: the U.S. Small Business Innovation Research Program (SBIR). *Small Business Economics* 20, pp. 129–135.

Audretsch, D.B. 2004. Sustaining innovation and growth: public policy support for entrepreneurship. *Industry and Innovation* 11(3), pp. 167–191.

Audretsch, D.B. and Lehmann, E.E. 2005. Does the knowledge spillover theory of entrepreneurship hold for regions? *Research Policy* 34(8), pp. 1191–1202.

Autio, E. et al. 2008. First- and second-order additionality and learning outcomes in collaborative R&D programs. *Research Policy* 37(1), pp. 59–76.

Ayyagari, M. et al. 2007. Small and medium enterprises across the globe. *Small Business Economics* 29(4), pp. 415–434.

Bahadir, S.C. et al. 2008. Financial value of brands in mergers and acquisitions: is value in the eye of the beholder? *Journal of Marketing* 72(6), pp. 49–64.

Baliga, B.R. et al. 1996. CEO duality and firm performance: what's the fuss? *Strategic Management Journal* 17(1), pp. 41–43.

Banerjee, P.M. and Campbell, B.A. 2009. Inventor bricolage and firm technology research and development. *R&D Management* 39(5), pp. 473–487.

Bantel, K.A. and Jackson, S.E. 1989. Top management and innovations in banking: does the composition of the top team make a difference? *Strategic Management Journal* 10(Special Issue), pp. 107–124.

Barnett, M.L. 2008. An attention-based view of real options reasoning. *Academy of Management Review* 33(3), pp. 606–628.

Barney, J. and Felin, T. 2013. What are microfoundations? *Academy of Management Perspectives* 27(2), pp. 138–155.

Barney, J.B. 1986. Strategic factor markets: expectations, luck, and business strategy. *Management Science* 32(10), pp. 1231–1241.

Barney, J.B. 1991. Firm resources and sustained competitive advantage. *Journal of Management* 17(1), pp. 99–120.

Barringer, M.W. and Milkovich, G.T. 1998. A theoretical exploration of the adoption and design of flexible benefit plans: a case of human resource innovation. *Academy of Management Review* 23(2), pp. 305–324.

Bascle, G. 2008. Controlling for endogeneity with instrumental variables in strategic management research. *Strategic Organization* 6(3), pp. 285–327.

Basdeo, D.K. et al. 2006. The impact of market actions on firm reputation. *Strategic Management Journal* 27(12), pp. 1205–1219.

Battese, G.E. and Coelli, T.J. 1992. Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. *Journal of Productivity Analysis* 3, pp. 153–169.

Battese, G.E. and Coelli, T.J. 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics* 20, pp. 325–332.

Baum, J.A.C. and Oliver, C. 1991. Institutional linkages and organizational mortality. *Administrative Science Quarterly* 36(2), pp. 187–218.

Baum, J.A.C. and Silverman, B.S. 2004. Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. *Journal of Business Venturing* 19(3), pp. 411–436.

Bayona-Saez, C. and Garcia-Marco, T. 2010. Assessing the effectiveness of the Eureka Program. *Research Policy* 39(10), pp. 1375–1386.

Beck, M. et al. 2016. Radical or incremental: where does R&D policy hit? *Research Policy* 45(4), pp. 869–883.

Beck, T. et al. 2005. SMEs, growth, and poverty: cross-country evidence. *Journal of Economic Growth* 10(3), pp. 199–229.

Beck, T. and Demirguc-Kunt, A. 2006. Small and medium-size enterprises: access to finance as a growth constraint. *Journal of Banking and Finance* 30(11), pp. 2931–2943.

Becker-Blease, J.R. and Sohl, J.E. 2015. New venture legitimacy: the conditions for angel investors. *Small Business Economics* 45(4), pp. 735–749.

Bekaert, G. et al. 2005. Does financial liberalization spur growth? *Journal of Financial Economics* 77(1), pp. 3–55.

Belderbos, R. et al. 2014. Multinationality and downside risk: the roles of option portfolio and organization. *Strategic Management Journal* 35, pp. 88–106.

Belderbos, R. and Zou, J.L. 2009. Real options and foreign affiliate divestments: a portfolio perspective. *Journal of International Business Studies* 40(4), pp. 600–620.

Bell, S.T. et al. 2011. Getting specific about demographic diversity variable and team performance relationships: a meta-analysis. *Journal of Management* 37(3), pp. 709–743.

Benner, M.J. and Tushman, M.L. 2002. Process management and technological innovation: a longitudinal study of the photography and paint industries. *Administrative Science Quarterly* 47(4), pp. 676–706.

Benner, M.J. and Waldfogel, J. 2008. Close to you? Bias and precision in patent-based measures of technological proximity. *Research Policy* 37(9), pp. 1556–1567.

Bercovitz, J. and Feldman, M.P. 2008. Academic entrepreneurs: organizational change at the individual level. *Organization Science* 19(1), pp. 69–89.

Bergek, A. and Bruzelius, M. 2010. Are patents with multiple inventors from different countries a good indicator of international R&D collaboration? The case of ABB. *Research Policy* 39(10), pp. 1321–1334.

Bergemann, D. and Hege, U. 1998. Venture capital financing, moral hazard, and learning. *Journal of Banking and Finance* 22(6–8), pp. 703–735.

Berger, J. et al. 1972. Status characteristics and social interaction. *American Sociological Review* 37(3), pp. 241–255.

Bertoni, F. et al. 2011. Venture capital financing and the growth of high-tech start-ups: disentangling treatment from selection effects. *Research Policy* 40(7), pp. 1028–1043.

Bertoni, F. and Tykvova, T. 2015. Does governmental venture capital spur invention and innovation? Evidence from young European biotech companies. *Research Policy* 44(4), pp. 925–935.

Bertrand, M. and Schoar, A. 2003. Managing with style: the effect of managers on firm policies. *Quarterly Journal of Economics* 118(4), pp. 1169–1208.

Bhattacharya, U. and Dittmar, A. 2001. *Costless versus costly signaling: theory and evidence from share purchases*. Working Paper. Indiana University, Bloomington.

Biddle, G.C. et al. 2009. How does financial reporting quality relate to investment efficiency? *Journal of Accounting and Economics* 48(2–3), pp. 112–131.

Bird, R.B. and Smith, E.A. 2005. Signaling theory, strategic interaction, and symbolic capital. *Current Anthropology* 46(2), pp. 221–248.

Birley, S. 1986. The role of new firms: births, deaths and job generation. *Strategic Management Journal* 7(4), pp. 361–376.

Birley, S. and Westhead, P. 1994. A taxonomy of business start-up reasons and their impact on firm growth and size. *Journal of Business Venturing* 9, pp. 7–31.

Black, F. and Scholes, M. 1973. The pricing of options and corporate liabilities. *Journal of Political Economy* 81, pp. 637–659.

Blind, K. et al. 2006. Motives to patent: empirical evidence from Germany. *Research Policy* 35(5), pp. 655–672.

Bloomberg 2015. Bloomberg visual data [Online] Available at: http://www.bloomberg.com/visual-data/ [Accessed: 12 November 2015].

Bock, R.D. 1975. *Multivariate statistical methods in behavioral research*. New York: McGraw-Hill.

Boente, W. 2004. Spillovers from publicly financed business R&D: Some empirical evidence from Germany. *Research Policy* 33(10), pp. 1635–1655.

Boh, W.F. et al. 2014. Balancing breadth and depth of expertise for innovation: a 3M story. *Research Policy* 43(2), pp. 349–366.

Boisot, M. and Canals, A. 2004. Data, information and knowledge: have we got it right? *Journal of Evolutionary Economics* 14(1), pp. 43–67.

Bollen, K.A. 1989. *Structural equations with latent variables*. New York: John Wiley & Sons.

Boone, C. et al. 2004. The genesis of top management team diversity: selective turnover among top management teams in Dutch newspaper publishing, 1970-94. *Academy of Management Journal* 47(5), pp. 633–656.

Booth, J.R. and Smith, R.L. 1986. Capital raising, underwriting and the certification hypothesis. *Journal of Financial Economics* 15(1–2), pp. 261–281.

Booz&Co 2012. The global innovation 1000: making ideas work. *strategy+business magazine*, pp. 1–14.

Bottazzi, G. et al. 2008. Productivity, profitability and financial performance. *Industrial and Corporate Change* 17(4), pp. 711–751.

Bottazzi, L. et al. 2008. Who are the active investors? Evidence from venture capital. *Journal of Financial Economics* 89(3), pp. 488–512.

Bouvard, M. 2012. Real option financing under asymmetric information. *Review of Financial Studies* 27(1), pp. 180–210.

Bowman, E.H. 1963. Consistency and optimality in managerial decision making. *Management Science* 9(2), pp. 310–321.

Bowman, E.H. and Hurry, D. 1993. Strategy through the option lens: an integrated view of resource investments and the incremental-choice process. *Academy of Management Review* 18(4), pp. 760–782.

Bowman, E.H. and Moskowitz, G.T. 2001. Real options analysis and strategic decision making. *Organization Science* 12(6), pp. 772–777.

Boyd, B.K. 1995. CEO duality and firm performance: a contingency model. *Strategic Management Journal* 16, pp. 301–312.

Boyd, D.E. et al. 2010. When do chief marketing officers affect firm value? A customer power explanation. *Journal of Marketing Research* XLVII(December), pp. 1162–1176.

Bradford, D.F. 1975. Constraints on government investment opportunities and the choice of discount rate. *American Economic Review* 65(5), pp. 887–899.

Brander, J.A. et al. 2002. Venture capital syndication: improved venture selection vs. the value-added hypothesis. *Journal of Economics & Management Strategy* 11(3), pp. 423–452.

Brander, J.A. et al. 2014. The effects of government-sponsored venture capital: international evidence. *Review of Finance* 19(2), pp. 571–618.

Branzei, O. et al. 2004. The formation of green strategies in Chinese firms: matching corporate environmental responses and individual principles. *Strategic Management Journal* 25(11), pp. 1075–1095.

Brennan, M.J. 1995. Corporate finance over the past 25 years. *Financial Management* 24(2), pp. 9–22.

Breusch, T.S. and Pagan, A.R. 1980. The Lagrange multiplier test and its applications to model specification in econometrics. *Review of Economic Studies* 47, pp. 239–253.

Brewer, A. 1987. Turgot: founder of classical economics. *Economica, New Series* 54(216), pp. 417–428.

Brown, J.R. et al. 2009. Financing innovation and growth: cash flow, external equity, and the 1990s R&D boom. *Journal of Finance* 64(1), pp. 151–185.

Brown, J.R. et al. 2012. Do financing constraints matter for R&D? *European Economic Review* 56(8), pp. 1512–1529.

Brown, J.R. et al. 2013. Law, stock markets, and innovation. *Journal of Finance* 68(4), pp. 1517–1549.

Brown, S.L. and Eisenhardt, K.M. 1997. The art of continuous change: linking complexity theory and time-paced evolution in relentlessly shifting organizations. *Administrative Science Quarterly* 42(1), pp. 1–34.

Brown, T.E. et al. 2001. An operationalization of Stevenson's conceptualization of entrepreneurship as opportunity-based firm behavior. *Strategic Management Journal* 22(10), pp. 953–968.

Brüderl, J. and Schüssler, R. 1990. Organizational mortality: the liabilities of newness and adolescence. *Administrative Science Quarterly* 35(3), pp. 530–547.

Bruton, G.D. et al. 2009. Founders, private equity investors, and underpricing in entrepreneurial IPOs. *Entrepreneurship Theory and Practice* 33(4), pp. 909–928.

Bryman, A. and Bell, E. 2011. *Business research methods*. 3rd ed. New York: Oxford University Press.

Bulan, L.T. 2005. Real options, irreversible investment and firm uncertainty: new evidence from U.S. firms. *Review of Financial Economics* 14(3–4), pp. 255–279.

Bunderson, S.J. 2003. Team member functional background and involvement in management teams: direct effects and the moderating role of power centralization. *Academy of Management Journal* 46(4), pp. 458–474.

Bunderson, S.J. and Sutcliffe, K.M. 2002. Comparing alternative conceptualizations of functional diversity in management teams: process and performance effects. *Academy of Management Journal* 45(5), pp. 875–893.

Burchardt, J. et al. 2016. Venture capital contracting in theory and practice: implications for entrepreneurship research. *Entrepreneurship Theory and Practice* (January), pp. 25–48.

Burke, A.E. et al. 2000. When less is more: distinguishing between entrepreneurial choice and performance. *Oxford Bulletin of Economics and Statistics* 62(5), pp. 565–587.

Burrell, G. and Morgan, G. 1979. *Sociological paradigms and organizational analysis*. Portsmouth, NH: Heinemann.

Burton, M.D. et al. 2002. Coming from good stock: career histories and new venture formation. In: Lounsbury, M. and Ventresca, M. eds. *Research in the Sociology of Organizations*. Greenwich, CN: JAI Press, pp. 229–262.

Busby, J.S. and Pitts, C.G.C. 1997. Real options in practice: an exploratory survey of how finance officers deal with flexibility in capital appraisal. *Management Accounting Research* 8, pp. 169–186.

Busenitz, L.W. et al. 2000. Country institutional profiles: unlocking entrepreneurial phenomena. *Academy of Management Journal* 43(5), pp. 994–1003.

Busenitz, L.W. et al. 2005. Signaling in venture capitalist—new venture decisions: does it indicate long-term venture outcomes? *Entrepreneurship Theory and Practice* January, pp. 1–12.

Butts, M.M. et al. 2015. Hot buttons and time sinks: the effects of electronic communication during nonwork time on emotions and work-nonwork conflict. *Academy of Management Journal* 58(3), pp. 763–788.

Byrne, O. and Shepherd, D.A. 2015. Different strokes for different folks: entrepreneurial narratives of emotion, cognition, and making sense of business failure. *Entrepreneurship Theory and Practice* 39(2), pp. 375–405.

Calderini, M. et al. 2007. If star scientists do not patent: the effect of productivity, basicness and impact on the decision to patent in the academic world. *Research Policy* 36(3), pp. 303–319.

Cannella, A.A.J. 2004. Editorial note. *Academy of Management Review* 29(1), p. 73.

Cannella, A.A.J. et al. 2008. Top management team functional background diversity and firm performance: examining the roles of team member colocation and environmental uncertainty. *Academy of Management Journal* 51(4), pp. 768–784.

Certo, S.T. et al. 2001. Signaling firm value through board structure: an investigation of initial public offerings. *Entrepreneurship Theory and Practice* 26(2), pp. 33–50.

Certo, S.T. 2003. Influencing initial public offering investors with prestige: signaling with board structures. *Academy of Management Review* 28(3), pp. 432–446.

Chambers, R.G. 1988. *Applied production analysis: a dual approach*. New York: Cambridge University Press.

Chandler, G.N. and Hanks, S.H. 1993. Measuring the performance of emerging businesses: a validation study. *Journal of Business Venturing* 8(5), pp. 391–408.

Chandler, G.N. and Hanks, S.H. 1994. Market attractiveness, resource-based capabilities, venture strategies, and venture performance. *Journal of Business Venturing* 9(4), pp. 331–349.

Chandy, R.K. et al. 2006. From invention to innovation: conversion in product development ability. *Journal of Marketing Research* 43(3), pp. 494–508.

Chang, S.J. 1995. International expansion strategy of Japanese firms: capability building through sequential entry. *Academy of Management Journal* 38(2), pp. 383–407.

Chang, S.J. and Rosenzweig, P.M. 1998. Industry and regional patterns in sequential foreign market entry. *Journal of Management Studies* 35(6), pp. 797–822.

Chatfield, C. 1995. *Problem solving: a statistician's guide*. 2nd ed. Boca Raton, Florida: Chapman & Hall/CRC.

Chatterjee, S. et al. 1999. Toward a strategic theory of risk premium: moving beyond CAPM. *Academy of Management Review* 24(3), pp. 556–567.

Chemmanur, T.J. et al. 2011. How does venture capital financing improve efficiency in private firms? A look beneath the surface. *Review of Financial Studies* 24(12), pp. 4037–4090.

Chevalier-Roignant, B. et al. 2011. Strategic investment under uncertainty: a synthesis. *European Journal of Operational Research* 215(3), pp. 639–650.

Cholakova, M. and Clarysse, B. 2015. Does the possibility to make equity investments in crowdfunding projects crowd out reward-based investments? *Entrepreneurship Theory and Practice* 39(1), pp. 145–172.

Churchill, G.A. and Iacobucci, D. 2002. *Marketing research: methodological foundations*. 8th ed. South Western.

Churchill, N.C. and Lewis, V.L. 1983. The five stages of small business growth. *Harvard Business Review* 61(3), pp. 30–50.

Clarysse, B. et al. 2011. Entrepreneurial origin, technological knowledge, and the growth of spin-off companies. *Journal of Management Studies* 48(6), pp. 1420–1442.

Coelli, T.J. et al. 2005. *An introduction to efficiency and productivity analysis*. 2nd ed. New York: Springer.

Coff, R. and Kryscynski, D. 2011. Drilling for micro-foundations of human capital-based competitive advantages. *Journal of Management* 37(5), pp. 1429–1443.

Coff, R.W. and Laverty, K.J. 2001. Real options on knowledge assets: panacea or pandora's box? *Business Horizons* 44(6), pp. 73–79.

Coff, R.W. and Laverty, K.J. 2007. Real options meet organizational theory: coping with path dependencies, agency costs, and organizational form. *Advances in Strategic Management* 24, pp. 333–361.

Cohen, B.D. and Dean, T.J. 2005. Information asymmetry and investor valuation of IPOs: top management team legitimacy as a capital market signal. *Strategic Management Journal* 26(7), pp. 683–690.

Cohen, J. 1992. A power primer. *Psychological Bulletin* 112(1), pp. 155–159.

Cohen, J. et al. 2003. *Applied multiple regression: correlation analysis for the behavioral sciences*. 3rd ed. Hillsdale, NJ: Lawrence Erlbaum Associates.

Cohen, M.D. et al. 1972. A garbage can model of organizational choice. *Administrative Science Quarterly* 17(1), pp. 1–25.

Cohen, W.M. and Levinthal, D.A. 1990. Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly* 35(1), pp. 128–152.

Coleman, M. and Liau, T.L. 1975. A computer readability formula designed for machine scoring. *Journal of Applied Psychology* 60(2), pp. 283–284.

Collis, D.J. 1994. Research note: how valuable are organizational capabilities? *Strategic Management Journal* 15, pp. 143–152.

Colombo, M.G. et al. 2015. Internal social capital and the attraction of early contributions in crowdfunding. *Entrepreneurship Theory and Practice* 39(1), pp. 75–100.

Connelly, B.L. et al. 2010. Signaling theory: a review and assessment. *Journal of Management* 37(1), pp. 39–67.

Conti, R. et al. 2014. Learning to be Edison: inventors, organizations, and breakthrough inventions. *Organization Science* 25(3), pp. 833–849.

Cooper, R.G. 2008. Perspective: the stage-gate idea-to-launch process—update, what's new, and next-gen systems. *Journal of Product Innovation Management* 25, pp. 213–232.

Cooper, R.G. and Kleinschmidt, E.J. 1986. An investigation into the new product process: steps, deficiencies, and impact. *Journal of Product Innovation Management* 3(2), pp. 71–85.

Cooper, R.S. 2003. Purpose and performance of the Small Business Innovation Research (SBIR) program. *Small Business Economics* 20, pp. 137–151.

Corbetta, P. 2003. *Social research: theory, methods and techniques*. Sage Publications.

Crawford, V.P. and Sobel, J. 1982. Strategic information transmission. *Econometrica* 50(6), pp. 1431–1451.

Croce, A. et al. 2013. The impact of venture capital on the productivity growth of European entrepreneurial firms: 'Screening' or 'value added' effect? *Journal of Business Venturing* 28(4), pp. 489–510.

Cui, A.S. and O'Connor, G. 2012. Alliance portfolio resource diversity and firm innovation. *Journal of Marketing* 76(July), pp. 24–43.

Cumming, D. 2006. Adverse selection and capital structure: evidence from venture capital. *Entrepreneurship Theory and Practice* 30(2), pp. 155–183.

Cumming, D. et al. 2014. *Governmental and independent venture capital investments in Europe: a firm-level performance analysis*. Working Paper.

Cumming, D. and Li, D. 2013. Public policy, entrepreneurship, and venture capital in the United States. *Journal of Corporate Finance* 23(November), pp. 345–367.

Custodio, C. et al. 2013. Generalists versus specialists: lifetime work experience and chief executive officer pay. *Journal of Financial Economics* 108(2), pp. 471–492.

Czarnitzki, D. and Toole, A.A. 2007. Business R&D and the interplay of R&D subsidies and product market uncertainty. *Review of Industrial Organization* 31, pp. 169–181.

Czarnitzki, D. and Toole, A.A. 2011. Patent protection, market uncertainty, and R&D investment. *Review of Economics and Statistics* 93(1), pp. 147–159.

Czarnitzki, D. and Toole, A.A. 2013. The R&D investment—uncertainty relationship: do strategic rivalry and firm size matter? *Managerial and Decision Economics* 34, pp. 15–28.

Daily, C.M. et al. 2005. Investment bankers and IPO pricing: does prospectus information matter? *Journal of Business Venturing* 20(1), pp. 93–111.

Dansereau, F. and Yammarino, F.J. 2003. Longitudinal processes in groups and organizations. *Group & Organization Management* 28(3), pp. 312–314.

Dansereau, F. and Yammarino, F.J. 2006. Is more discussion about levels of analysis really necessary? When is such discussion sufficient? *Leadership Quarterly* 17(5), pp. 537–552.

Darby, M.R. and Zucker, L.G. 2003. Growing by leaps and inches: creative destruction, real cost reduction, and inching up. *Economic Inquiry* 41(1), pp. 1–19.

Dasgupta, P. and David, P.A. 1994. Toward a new economics of science. *Research Policy* 23(5), pp. 487–521.

Datta, S. and Iskandar-Datta, M. 2014. Upper-echelon executive human capital and compensation: generalist vs specialist skills. *Strategic Management Journal* 35(12), pp. 1853–1866.

David, P.A. et al. 2000. Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy* 29(4–5), pp. 497–529.

David, P.A. and Hall, B.H. 2000. Heart of darkness: modeling public–private funding interactions inside the R&D black box. *Research Policy* 29(9), pp. 1165–1183.

Davidsson, P. and Honig, B. 2003. The role of social and human capital among nascent entrepreneurs. *Journal of Business Venturing* 18(3), pp. 301–331.

Davidsson, P. and Wiklund, J. 2000. Conceptual and empirical challenges in the study of firm growth. In: Sexton, D. and Landstrom, H. eds. *The Blackwell Handbook of Entrepreneurship*. pp. 26 – 44.

Davila, A. et al. 2003. Venture capital financing and the growth of startup firms. *Journal of Business Venturing* 18(6), pp. 689–708.

Day, G.S. 1994. The capabilities of market-drive organizations. *Journal of Marketing* 58(4), pp. 37–52.

Dean, B. V. and Giglierano, J.J. 1990. Multistage financing of technical start-up companies in silicon valley. *Journal of Business Venturing* 5(6), pp. 375–389.

DeCarolis, D. et al. 2009. Weathering the storm: the benefit of resources to high-technology ventures navigating adverse events. *Strategic Entrepreneurship Journal* 160, pp. 147–160.

Deeds, D.L. et al. 1997. The impact of firm-specific capabilities on the amount of capital raised in an initial public offering: evidence from the biotechnology industry. *Journal of Business Venturing* 12(1), pp. 31–46.

Deeds, D.L. et al. 1999. Dynamic capabilities and new product development in high technology ventures: an empirical analysis of new biotechnology firms. *Journal of Business Venturing* 15, pp. 211–229.

Deeds, D.L. 2001. Role of R&D intensity, technical development and absorptive capacity in creating entrepreneurial wealth in high technology start-ups. *Journal of Engineering and Technology Management* 18(1), pp. 29–47.

Deeds, D.L. et al. 2004. The influence of firms’ and industries’ legitimacy on the flow of capital into high-technology ventures. *Strategic Organization* 2(1), pp. 9–34.

DeKinder, J.S. and Kohli, A.K. 2008. Flow signals: how patterns over time affect the acceptance of start-up firms. *Journal of Marketing* 72(5), pp. 84–97.

Delmar, F. 1997. Measuring growth: methodological considerations and empirical results. In: Donckels, R. and Miettinen, A. eds. *Entrepreneurship and SME Research: On its Way to the Next Millennium*. pp. 199 – 216.

Delmar, F. et al. 2003. Arriving at the high-growth firm. *Journal of Business Venturing* 18(2), pp. 189–216.

Denrell, J. 2004. Random walks and sustained competitive advantage. *Management Science* 50(7), pp. 922–934.

Denrell, J. 2005. Selection bias and the perils of benchmarking. *Harvard Business Review* 83(4), pp. 114–119.

Denrell, J. et al. 2013. Inferring superior capabilities from sustained superior perofrmance: a Bayesian analysis. *Strategic Management Journal* 34, pp. 182–196.

Desarbo, W. et al. 1987. Criteria for corporate venturing: importance assigned by managers. *Journal of Business Venturing* 2(4), pp. 329–350.

Deshpande, R. 1983. 'Paradigms lost': on theory and method in research in marketing. *Journal of Marketing* 47(4 (Autumn)), pp. 101–110.

Dimos, C. and Pugh, G. 2016. The effectiveness of R&D subsidies: a meta-regression analysis of the evaluation literature. *Research Policy* 45(4), pp. 797–815.

Ding, M. and Eliashberg, J. 2002. Structuring the new product development pipeline. *Management Science* 48(3), pp. 343–363.

Ding, W.W. 2011. The impact of founders' professional-education background on the adoption of open science by for-profit biotechnology firms. *Management Science* 57(2), pp. 257–273.

DiPrete, T.A. and Eirich, G.M. 2006. Cumulative advantage as a mechanism for inequality: a review of theoretical and empirical developments. *Annual Review of Sociology* 32(1), pp. 271–297.

Dixit, A.K. 1989. Entry and exit decisions under uncertainty. *Journal of Political Economy* 97, pp. 620–638.

Dixit, A.K. 1992. Investment and hysteresis. *Journal of Economic Perspectives* 6(1), pp. 107–132.

Dixit, A.K. and Pindyck, R.S. 1994. *Investment under uncertainty*. Princeton, NJ: Princeton University Press.

Dixit, A.K. and Pindyck, R.S. 1995. The options approach to capital investment. *Harvard Business Review* May-June, pp. 105–115.

Dokko, G. and Gaba, V. 2012. Venturing into new territory: career experiences of corporate venture capital managers and practice variation. *Academy of Management Journal* 55(3), pp. 563–583.

Donaldson, L. 1996. *For positivist organization theory*. London: Sage.

Donaldson, L. 2005. Vita contemplativa: following the scientific method: how i became a committed functionalist and positivist. *Organization Studies* 26(7), pp. 1071–1088.

Dosi, G. and Nelson, R.R. 2010. Technical change and industrial dynamics as evolutionary processes. In: Hall, B. H. and Rosenberg, N. eds. *Handbook of the Economics of Innovation, Vol. 1*. Amsterdam: North Holland, pp. 51–127.

Dotzel, T. et al. 2013. Service innovativeness and firm value. *Journal of Marketing* L(April), pp. 259–276.

Driouchi, T. and Bennett, D.J. 2011. Real options in multinational decision-making: managerial awareness and risk implications. *Journal of World Business* 46(2), pp. 205–219.

Driouchi, T. and Bennett, D.J. 2012. Real options in management and organizational strategy: a review of decision-making and performance implications. *International Journal of Management Reviews* 14(1), pp. 39–62.

Durand, R. 2002. Competitive advantages exist: a critique of Powell. *Strategic Management Journal* 23(9), pp. 867–872.

Durand, R. and Vaara, E. 2009. Causation, counterfactuals, and competitive advantage. *Strategic Management Journal* 30(12), pp. 1245–1264.

Durcikova, A. and Gray, P. 2009. How knowledge validation processes affect knowledge contribution. *Journal of Management Information Systems* 25(4), pp. 81–108.

Dutta, S. et al. 1999. Success in high-technology markets: is marketing capability critical? *Marketing Science* 18(4), pp. 547–568.

Dutta, S. et al. 2005. Conceptualizing and measuring capabilities: methodology and empirical application. *Strategic Management Journal* 26(3), pp. 277–285.

Dutta, S. and Folta, T.B. 2016. A comparison of the effect of angels and venture capitalists on innovation and value creation. *Journal of Business Venturing* 31(1), pp. 39–54.

Dutta, S. and Weiss, A.M. 1997. The relationship between a firm's level of technological innovativeness and its pattern of partnership agreements. *Management Science* 43(3), pp. 343–356.

Ebben, J.J. and Johnson, A.C. 2005. Efficiency, flexibility, or both? Evidence linking strategy to performance in small firms. *Strategic Management Journal* 26(13), pp. 1249–1259.

Eberhart, R.N. et al. 2014. *Compensating conformity: resolving the tension between economic incentives and organizational legitimacy in entrepreneurship*. Working Paper. Stanford University.

Eckhardt, J.T. et al. 2006. Multistage selection and the financing of new ventures. *Management Science* 52(2), pp. 220–232.

Edler, J. and Georghiou, L. 2007. Public procurement and innovation—resurrecting the demand side. *Research Policy* 36(7), pp. 949–963.

Ehrhart, K.H. and Ziegert, J.C. 2005. Why are individuals attracted to organizations? *Journal of Management* 31(6), pp. 901–919.

Eisenhardt, K.M. 1988. Agency- and institutional-theory explanations: the case of retail sales compensation. *Academy of Management Journal* 31(3), pp. 488–511.

Eisenhardt, K.M. et al. 2010. Microfoundations of performance: balancing efficiency and flexibility in dynamic environments. *Organization Science* 21(6), pp. 1263–1273.

Eisenhardt, K.M. and Schoonhoven, C.B. 1990. Organizational growth: linking founding team, strategy, environment, and growth among U.S. semiconductor ventures. *Administrative Science Quarterly* 35(3), pp. 504–529.

Eisenhardt, K.M. and Tabrizi, B.N. 1995. Accelerating adaptive processes: product innovation in the global computer industry. *Administrative Science Quarterly* 40(1), pp. 84–110.

Elitzur, R. and Gavious, A. 2003. Contracting, signaling, and moral hazard: a model of entrepreneurs, 'angels', and venture capitalists. *Journal of Business Venturing* 18(6), pp. 709–725.

Elsevier 2015. About the h-index [Online] Available at: http://help.elsevier.com/app/answers/detail/a_id/2876/p/8150/kw/h-index/search/1 [Accessed: 15 November 2015].

Elston, J.A. and Audretsch, D.B. 2010. Risk attitudes, wealth and sources of entrepreneurial start-up capital. *Journal of Economic Behavior and Organization* 76(1), pp. 82–89.

Elston, J.A. and Audretsch, D.B. 2011. Financing the entrepreneurial decision: an empirical approach using experimental data on risk attitudes. *Small Business Economics* 36(2), pp. 209–222.

Ensley, M.D. et al. 2002. Understanding the dynamics of new venture top management teams: cohesion, conflict, and new venture performance. *Journal of Business Venturing* 17(4), pp. 365–386.

Ensley, M.D. and Hmieleski, K.M. 2005. A comparative study of new venture top management team composition, dynamics and performance between university-based and independent start-ups. *Research Policy* 34(7), pp. 1091–1105.

Ethiraj, S.K. et al. 2005. Where do capabilities come from and how do they matter? A study in the software services industry. *Strategic Management Journal* 26(1), pp. 25–45.

Etzkowitz, H. 1998. The norms of entrepreneurial science: cognitive effects of the new university–industry linkages. *Research Policy* 27(8), pp. 823–833.

Ewens, M. et al. 2015. *Cost of experimentation and the evolution of venture capital*. Working Paper.

Fama, E.F. and French, K.R. 1997. Industry costs of equity. *Journal of Financial Economics* 43(2), pp. 153–193.

Farrell, J. and Rabin, M. 1996. Cheap talk. *Journal of Economic Perspectives* 10(3), pp. 103–118.

Feldman, M.P. and Kelley, M.R. 2006. The ex ante assessment of knowledge spillovers: government R&D policy, economic incentives and private firm behavior. *Research Policy* 35(10), pp. 1509–1521.

Feng, H. et al. 2015. Marketing department power and firm performance. *Journal of Marketing* 79(5), pp. 1–20.

Ferguson, A.J. et al. 2016. Misfit and milestones: structural elaboration and capability reinforcement in the evolution of entrepreneurial top management teams. *Academy of Management Journal* 59(4), pp. 1430–1450.

Filatotchev, I. and Bishop, K. 2002. Board composition, share ownership, and 'underpricing' of U.K. IPO firms. *Strategic Management Journal* 23(10), pp. 941–955.

Finkelstein, S. and D'Aveni, R.A. 1994. CEO duality as a double-edged sword: how boards of directors balance entrenchment avoidance and unity of command. *Academy of Management Journal* 37(5), pp. 1079–1108.

Finkelstein, S. and Hambrick, D.C. 1989. Chief executive compensation: a study of the intersection of markets and political processes. *Strategic Management Journal* 10(2), pp. 121–134.

Finkelstein, S. and Hambrick, D.C. 1990. Top-management team tenure and organizational outcomes: the moderating role of managerial discretion. *Administrative Science Quarterly* 35, pp. 484–503.

Fiske, S.T. and Taylor, S.E. 1991. *Social cognition*. 2nd ed.

Flesch, R. 1948. A new readability yardstick. *Journal of Applied Psychology* 32(3), pp. 221–233.

Folta, T.B. et al. 2006. Uncertainty, irreversibility, and the likelihood of entry: an empirical assessment of the option to defer. *Journal of Economic Behavior and Organization* 61, pp. 432–452.

Folta, T.B. and Miller, K.D. 2002. Real options in equity partnerships. *Strategic Management Journal* 23(1), pp. 77–88.

Folta, T.B. and O'Brien, J.P. 2004. Entry in the presence of dueling options. *Strategic Management Journal* 25(2), pp. 121–138.

Fombrun, C. and Shanley, M. 1990. What's in a name? Reputation building and corporate strategy. *Academy of Management Journal* 33(2), pp. 33–58.

Forbes 2014. Private-company growth slowed in 2013 [Online] Available at: http://www.forbes.com/sites/sageworks/2014/02/02/private-company-growth-slowed-in-2013/ [Accessed: 10 November 2015].

Fortune, A. and Mitchell, W. 2012. Unpacking firm exit at the firm and industry levels: the adaptation and selection of firm capabilities. *Strategic Management Journal* 33, pp. 794–819.

Foss, N.J. 2011. Why micro-foundations for resource-based theory are needed and what they may look like. *Journal of Management* 37(5), pp. 1413–1428.

Freear, J. et al. 1994. Angels and non-angels: are there differences? *Journal of Business Venturing* 9(2), pp. 109–123.

Fried, H.O. et al. 2008. Efficiency and productivity. In: Fried, H. O. et al. eds. *The Measurement of Productive Efficiency and Productivity Growth*. New York: Oxford University Press, pp. 3–91.

Gartner, W.B. 1985. A conceptual framework for describing the phenomenon of new venture creation. *Academy of Management Review* 10(4), pp. 696–706.

Gartner, W.B. et al. 1992. Acting as if: differentiating entrepreneurial from organizational behavior. *Entrepreneurship Theory and Practice* 16(3), pp. 13–31.

Gartner, W.B. and Shane, S.A. 1995. Measuring entrepreneurship over time. *Journal of Business Venturing* 10(4), pp. 283–301.

Gavetti, G. and Levinthal, D.A. 2000. Looking forward and looking backward: cognitive and experiential search. *Administrative Science Quarterly* 45(1), pp. 113–137.

Geletkanycz, M.A. and Black, S.S. 2001. Bound by the past? Experience-based effects on commitment to the strategic status quo. *Journal of Management* 27(1), pp. 3–21.

Georghiou, L. 2002. Additionality and impact of R&D subsidies. *IWT Studies* 40, pp. 57–64.

Ghauri, P.N. and Gronhaug, K. 2002. *Research methods in business studies*. 2nd ed. Harlow: Pearson Education.

Ghemawat, P. and Costa, J.E.R.I. 1993. The organizational tension between static and dynamic efficiency. *Strategic Management Journal* 14, pp. 59–73.

Gilbert, B.A. et al. 2006. New venture growth: a review and extension. *Journal of Management* 32(6), pp. 926–950.

Gill, J. and Johnson, P. 1997. *Research methods for managers*. 2nd ed. London: Paul Chapman Publishing.

Gimeno, J. et al. 1997. Survival of the fittest? Entrepreneurial human capital and the persistence of underperforming firms. *Administrative Science Quarterly* 42(4), pp. 750–783.

Gimmon, E. and Levie, J. 2010. Founder's human capital, external investment, and the survival of new high-technology ventures. *Research Policy* 39(9), pp. 1214–1226.

Gioia, D.A. and Chittipeddi, K. 1991. Sensemaking and sensegiving in strategic change initiation. *Strategic Management Journal* 12(6), pp. 433–448.

Gioia, D.A. and Pitre, E. 1990. Multiparadigm perspectives on theory building. *Academy of Management Review* 15, pp. 584–602.

Girotra, K. et al. 2007. Valuing R&D projects in a potfolio: evidence from the pharmaceutical industry. *Management Science*, pp. 2–9.

Gittelman, M. and Kogut, B. 2003. Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns. *Management Science* 49(4), pp. 366–382.

Glynn, M.A. 1996. Innovative genius: a framework for relating individual and organizational intelligences to innovation. *Academy of Management Review* 21(4), pp. 1081–1111.

Gompers, P.A. 1995. Optimal investment, monitoring, and the staging of venture capital. *Journal of Finance* 50(5), pp. 1461–1489.

Gompers, P.A. and Lerner, J. 2000. Money chasing deals? The impact of fund inflows on private equity valuations. *Journal of Financial Economics* 55(2), pp. 281–325.

Gomulya, D. and Boeker, W. 2014. How firms respond to financial restatement: CEO successors and external reactions. *Academy of Management Journal* 57(6), pp. 1759–1785.

Goolsbee, A. 1998. Does government R&D policy mainly benefit scientists and engineers? *Tax and Human-Capital Policy* 88(2), pp. 298–302.

Goranova, M. et al. 2007. Managerial ownership and corporate diversification: a longitudinal view. *Strategic Management Journal* 28(3), pp. 211–225.

Graffin, S.D. et al. 2013. Examining CEO succession and the role of heuristics in early-stage CEO evaluation. *Strategic Management Journal* 34(4), pp. 383–403.

Granstrand, O. 1999. *The economics and management of intellectual property: towards intellectual capitalism*. Cheltenham/UK, and Northampton/USA: Edward Elgar.

Greene, W.H. 2008. The econometric approach to efficiency analysis. In: Fried, H. O. et al. eds. *The Measurement of Productive Efficiency and Productivity Growth*. New York: Oxford University Press, pp. 92–250.

Greene, W.H. 2012. *Econometric analysis*. 7th ed. Upper Saddle River, NJ: Prentice Hall.

Griffin, A. 1997. PDMA research on new product development practices: updating trends and benchmarking best practices. *Journal of Product Innovation Management* 14(6), pp. 429–458.

Griffin, D.W. and Varey, C.A. 1996. Towards a consensus on overconfidence. *Organizational Behavior and Human Decision Processes* 65(3), pp. 227–231.

Grigoriou, K. and Rothaermel, F.T. 2014. Structural microfoundations of innovation: the role of relational stars. *Journal of Management* 40(2), pp. 586–615.

Griliches, Z. 1990. Patent statistics as economic indicators: a survey. *Journal of Economic Literature* 28(4), pp. 1661–1707.

Griliches, Z. 1992. The search for R&D spillovers. *Scandinavian Journal of Economics* 94, pp. 29–47.

Grilli, L. and Murtinu, S. 2011. *Turning European new technology-based firms into 'gazelles': the role of public (and private) venture capital*. Working Paper.

Grilli, L. and Murtinu, S. 2013. *New technology-based firms in Europe: market penetration, public venture capital and timing of investment*. Working Paper.

Grilli, L. and Murtinu, S. 2014. Government, venture capital and the growth of European high-tech entrepreneurial firms. *Research Policy* 43(9), pp. 1523–1543.

Groh, A.P. et al. 2010. The European venture capital and private equity country attractiveness indices. *Journal of Corporate Finance* 16(2), pp. 205–224.

Gruber, M. et al. 2013. Knowledge recombination across technological boundaries: scientists vs. engineers. *Management Science* 59(4), pp. 837–851.

Grupp, H. and Schmoch, U. 1999. Patent statistics in the age of globalisation: new legal procedures, new analytical methods, new economic interpretation. *Research Policy* 28(4), pp. 377–396.

Guan, J. and Chen, K. 2012. Modeling the relative efficiency of national innovation systems. *Research Policy* 41(1), pp. 102–115.

Guedj, I. and Scharfstein, D. 2004. *Organizational scope and investment: evidence from the drug development strategies of biopharmaceutical firms*. Working Paper.

Guerrero, M. and Urbano, D. 2014. Academics' start-up intentions and knowledge filters: an individual perspective of the knowledge spillover theory of entrepreneurship. *Small Business Economics* 43(1), pp. 57–74.

Gulati, R. and Higgins, M.C. 2003. Which ties matter when? The contingent effects of interorganizational partnerships on IPO success. *Strategic Management Journal* 24(2), pp. 127–144.

Guler, I. 2007a. An empirical examination of management of real options in the U.S. venture capital industry. *Advances in Strategic Management* 24, pp. 485–506.

Guler, I. 2007b. Throwing good money after bad? Political and institutional influences on sequential decision making in the venture capital industry. *Administrative Science Quarterly* 52, pp. 248–285.

Gunning, R. 1952. *The technique of clear writing*. New York: McGraw-Hill.

Gupta, A.K. et al. 2006. The interplay between exploration and exploitation. *Academy of Management Journal* 49(4), pp. 693–706.

Haeussler, C. et al. 2014. How patenting informs VC investors - the case of biotechnology. *Research Policy* 43(8), pp. 1286–1298.

Hahn, E.D. and Doh, J.P. 2006. Using Bayesian methods in strategy research: an extension of Hansen et al. *Strategic Management Journal* 27(8), pp. 783–798.

Hair, J.F. et al. 2010. *Multivariate data analysis: a global perspective*. 7th ed. Upper Saddle River, NJ: Pearson Prentice Hall.

Haleblian, J. and Finkelstein, S. 1993. Top management team size, CEO dominance, and firm performance: the moderating roles of environmental turbulence and discretion. *Academy of Management Journal* 36(4), pp. 844–863.

Hall, B.H. and Lerner, J. 2010. The financing of R&D and innovation. In: Hall, B. and N., R. eds. *Handbook of the Economics of Innovation*. Netherlands: Elsevier, pp. 609–639.

Hall, R. 1993. A framework linking intangible resources and capabilities to sustainable competitive advantage. *Strategic Management Journal* 14(8), pp. 607–618.

Hambrick, D.C. and Fukutomi, G.D. 1991. The seasons of a CEO's tenure. *Academy of Management Review* 16(4), pp. 719–742.

Hamilton, B.H. and Nickerson, J.A. 2003. Correcting for endogeneity in strategic management research. *Strategic Organization* 1(1), pp. 51–78.

Han, X. and Niosi, J. 2016. Star scientists in PV technology and the limits of academic entrepreneurship. *Journal of Business Research* 69(5), pp. 1707–1711.

Hannan, M.T. and Freeman, J. 1984. Structural inertia and organizational change. *American Sociological Review* 49(2), pp. 149–164.

Hansen, M.H. et al. 2004. A Bayesian operationalization of the resource-based view. *Strategic Management Journal* 25(13), pp. 1279–1295.

Hargadon, A. and Sutton, R.I. 1997. Technology brokering and innovation in a product development firm. *Administrative Science Quarterly* 42(4), pp. 716–749.

Harris, D. and Helfat, C.E. 1997. Specificity of CEO human capital and compensation. *Strategic Management Journal* 18(11), pp. 895–920.

Harvey, M.G. and Lusch, R.F. 1995. Expanding the nature and scope of due diligence. In: *Journal of Business Venturing*. pp. 5–21.

Hauser, J. et al. 2006. Research on innovation: a review and agenda for marketing science. *Marketing Science* 25(6), pp. 687–717.

Hausman, J.A. 1978. Specification tests in econometrics. *Econometrica: Journal of the Econometric Society* 46(6), pp. 1251–1271.

Hayek, F.A. 1945. The use of knowledge in society. *American Economic Review* 35(4), pp. 519–530.

Heeley, M.B. et al. 2007. Innovation, appropriability, and the underpricing of initial public offerings. *Academy of Management Journal* 50(1), pp. 209–225.

Heil, O. and Robertson, T.S. 1991. Toward a theory of competitive market signaling: a research agenda. *Strategic Management Journal* 12(6), pp. 403–418.

Helfat, C.E. and Martin, J.A. 2015. Dynamic managerial capabilities: review and assessment of managerial impact on strategic change. *Journal of Management* 41(5), pp. 1281–1312.

Helfat, C.E. and Winter, S.G. 2011. Untangling dynamic and operational capabilities: strategy for the (n)ever-changing world. *Strategic Management Journal* 32, pp. 1243–1250.

Hellmann, T.F. and Puri, M. 2002. Venture capital and the professionalization of start-up firms: empirical evidence. *Journal of Finance* 57(1), pp. 169–197.

Henderson, R.M. and Clark, K.B. 1990. Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly* 35(1), pp. 9–30.

Henderson, R.M. and Cockburn, I. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal* 15, pp. 63–84.

Heracleous, L. and Jacobs, C.D. 2008. Understanding organizations through embodied metaphors. *Organization Studies* 29(1), pp. 45–78.

Higgins, M.C. and Gulati, R. 2006. Stacking the deck: the effects of top management backgrounds on investor decisions. *Strategic Management Journal* 27(1), pp. 1–25.

Higgins, M.J. et al. 2011. Conveying quality and value in emerging industries: star scientists and the role of signals in biotechnology. *Research Policy* 40(4), pp. 605–617.

Hillman, A.I. and Dalziel, T. 2003. Boards of directors and firm-performance: integrating agency and resource dependence perspectives. *Academy of Management Review* 28(3), pp. 383–396.

Hirsch, J.E. 2005. An index to quantify an individual's scientific research output. *Proceedings of the National Academy of Sciences of the United States of America* 102(46), pp. 16569–16572.

Hitt, M.A. et al. 2001. Direct and moderating effects of human capital on strategy and performance in professional service firms: a resource-based perspective. *Academy of Management Journal* 44(1), pp. 13–28.

Hitt, M.A. and Tyler, B.B. 1991. Strategic decision models: integrating different perspectives. *Strategic Management Journal* 12, pp. 327–351.

Hollis, M. 2006. *The philosophy of social science: an introduction*. 4th ed. Cambridge University Press.

Homburg, C. et al. 2014. The role of chief marketing officers for venture capital funding: endowing new ventures with marketing legitimacy. *Journal of Marketing Research* 51(5), pp. 625–644.

Honaker, J. et al. 2012. Amelia II: a program for missing data. *Journal Of Statistical Software* 45(7), pp. 1–57.

Honaker, J. and King, G. 2010. What to do about missing values in time-series cross-section data. *American Journal of Political Science* 54(2), pp. 561–581.

Hoskisson, R.E. et al. 2011. Revitalizing entrepreneurship: the search for new research opportunities. *Journal of Management Studies* 48(6), pp. 1141–1168.

Hottenrott, H. and Lopes-Bento, C. 2014. (International) R&D collaboration and SMEs: The effectiveness of targeted public R&D support schemes. *Research Policy* 43(6), pp. 1055–1066.

Howell, S.D. and Jaegle, A.J. 1997. Laboratory evidence on how managers intuitively value real growth options. *Journal of Business Finance & Accounting* 24(7&8), pp. 915–935.

Howell, S.T. 2015. Financing constraints as barriers to innovation: evidence from R&D grants to energy startups. PhD Thesis, Harvard University.

Hoy, F. et al. 1992. Strategies and environments of high growth firms. In: Sexton, D.L., Kasarda, J. D. ed. *The State of the Art of Entrepreneurship*. Boston: PWS-Kent Publishing, pp. 341 – 357.

Hsu, D.H. 2006. Venture capitalists and cooperative start-up commercialization strategy. *Management Science* 52(2), pp. 204–219.

Hsu, D.H. 2007. Experienced entrepreneurial founders, organizational capital, and venture capital funding. *Research Policy* 36(5), pp. 722–741.

Hsu, D.H. and Ziedonis, R.H. 2013. Resources as dual sources of advantage: implications for valuing entrepreneurial-firm patents. *Strategic Management Journal* 34(7), pp. 761–781.

Hsu, L.-C. and Wang, C.-H. 2012. Clarifying the effect of intellectual capital on performance: the mediating role of dynamic capability. *British Journal of Management* 23(2), pp. 179–205.

Hsu, P.-H. et al. 2014. Financial development and innovation: cross-country evidence. *Journal of Financial Economics* 112(1), pp. 116–135.

Huber, G.P. 1991. Organizational learning: the contributing process and the literatures. *Organization Science* 2(1), pp. 88–115.

Hughes, P. et al. 2010. Why do product-market strategies fail? A sociostructural examination under conditions of adherence. *Group & Organization Management* 35(5), pp. 606–635.

Hunt, C.S. and Aldrich, H.E. 1996. Why even Rodney Dangerfield has a home page: legitimizing the world wide web as a medium for commercial endeavors. In: *Annual Meeting of the Academy of*

Management. Cincinnati, OH.

Hunt, S.D. 1983. General theories and the fundamental explananda of marketing. *Journal of Marketing* 47(Fall), pp. 9–17.

Hunt, S.D. 1993. Objectivity in marketing theory and research. *Journal of Marketing* 57(2), pp. 76–91.

Hurry, D. et al. 1992. Calls on high-technology: Japanese exploration of venture capital investments in the United States. *Strategic Management Journal* 13(2), pp. 85–101.

Hurry, D. 1993. Restructuring in the global economy: the consequences of strategic linkages between Japanese and U.S. firms. *Strategic Management Journal* 14, pp. 69–82.

Iansiti, M. and Clark, K.B. 1994. Integration and dynamic capability: evidence from product development in automobiles and mainframe computers. *Industrial and Corporate Change* 3(3), pp. 557–605.

Ilmola, L. and Kuusi, O. 2006. Filters of weak signals hinder foresight: monitoring weak signals efficiently in corporate decision-making. *Futures* 38(8), pp. 908–924.

Irwin, D.A. and Klenow, P.J. 1994. Learning-by-doing spillovers in the semiconductor industry. *Journal of Political Economy* 102(6), p. 1200.

Jaffe, A.B. 1989. Real effects of academic research. *American Economic Review* 79(5), pp. 957–970.

Jain, B.A. et al. 2008. The path-to-profitability of Internet IPO firms. *Journal of Business Venturing* 23(2), pp. 165–194.

Janney, J.J. and Dess, G.G. 2004. Can real-options analysis improve decision-making? Promises and pitfalls. *Academy of Management Executive* 18(4), pp. 60–75.

Janney, J.J. and Folta, T.B. 2003. Signaling through private equity placements and its impact on the valuation of biotechnology firms. *Journal of Business Venturing* 18(3), pp. 361–380.

Janney, J.J. and Folta, T.B. 2006. Moderating effects of investor experience on the signaling value of private equity placements. *Journal of Business Venturing* 21(1), pp. 27–44.

Jeng, L.A. and Wells, P.C. 2000. The determinants of venture capital funding: evidence across countries. *Journal of Corporate Finance* 6(3), pp. 241–289.

Jensen, K. and Warren, P. 2001. The use of options theory to value research in the service sector. *R&D Management* 31(2), pp. 173–180.

Jensen, M.C. 1989. Active investors, LBOS, and the privatization of bankruptcy. *Journal of Applied Corporate Finance* 2(1), pp. 35–44.

Jensen, R. and Thursby, M.C. 2001. Proofs and prototypes for sale: the licensing of university inventions. *American Economic Review* 91(1), pp. 240–259.

Jones, C.I. and Williams, J.C. 1998. Measuring the social return to R&D. *Quarterly Journal of Economics* 113(4), pp. 1119–1135.

Kaplan, S.N. and Schoar, A. 2005. Private equity performance: returns, persistence, and capital flows. *Journal of Finance* 60(4), pp. 1791–1824.

Kaplan, S.N. and Stroemberg, P. 2004. Characteristics, contracts, and actions: evidence from venture capitalist analyses. *Journal of Finance* 59(5), pp. 2177–2210.

Karna, A. et al. 2016. Revisiting the role of the environment in the capabilities-financial performance relationship: a meta-analysis. *Strategic Management Journal* 37(6), pp. 1154–1173.

Katz, R.L. 1982. The effects of group longevity on project communication and performance. *Administrative Science Quarterly* 27, pp. 81–105.

Kehoe, R.R. and Tzabbar, D. 2015. Lighting the way or stealing the shine? An examination of the duality in star scientists' effects on firm innovative performance. *Strategic Management Journal* 36(5), pp. 709–727.

Kennedy, P. 2003. *A guide to econometrics*. 5th ed. Blackwell Publishing.

Kenneth R. French 2015. Kenneth R. French's data library [Online] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html [Accessed: 10 November 2015].

Kerr, W.R. et al. 2014. Entrepreneurship as experimentation. *Journal of Economic Perspectives* 28(3), pp. 25–48.

Kerr, W.R. and Nanda, R. 2014. *Financing innovation*. Working Paper. Harvard Business School Division of Research.

Kester, W.C. 1984. Today options for tomorrow's growth. *Harvard Business Review* 62(2), pp. 153–160.

Khaire, M. 2010. Young and no money? Never mind: the material impact of social resources on new venture growth. *Organization Science* 21(1), pp. 168–185.

Khurana, A. and Rosenthal, S.R. 1997. Integrating the fuzzy front end of new product development. *MIT Sloan Management Review* 38(2), pp. 103–120.

Khurana, A. and Rosenthal, S.R. 1998. Towards holistic 'front ends' in new product development. *Journal of Product Innovation Management* 15, pp. 57–74.

Kiesler, S.B. 1975. Actuarial prejudice toward women and its implications. *Journal of Applied Social Psychology* 5(3), pp. 201–206.

King, G. et al. 2001. Analyzing incomplete political science data. *American Political Science Review* 85(1269), pp. 49–69.

King, R.G. and Levine, R. 1993a. Finance, entrepreneurship, and growth: theory and evidence. *Journal of Monetary Economics* 32, pp. 513–542.

King, R.G. and Levine, R. 1993b. Finance and growth: Schumpeter might be right. *Quarterly Journal of Economics* 108(3), pp. 717–737.

Kirsch, D. et al. 2009. Form or substance: the role of business plans in venture capital decision making. *Strategic Management Journal* 30, pp. 487–515.

Kish-Gephart, J.J. and Campbell, J.T. 2015. You don't forget your roots: the influence of CEO social class background on strategic risk taking. *Academy of Management Journal* 58(6), pp. 1614–1636.

Klapper, L. et al. 2006. Entry regulation as a barrier to entrepreneurship. *Journal of Financial Economics* 82(3), pp. 591–629.

Kleer, R. 2010. Government R&D subsidies as a signal for private investors. *Research Policy* 39(10), pp. 1361–1374.

Klein, K.J. and Kozlowski, S.W.J. 2000. From micro to meso: critical steps in conceptualizing and conducting multilevel research. *Organizational Research Methods* 3(3), pp. 211–236.

Klein, P.G. et al. 2014. The effects of alternative investments on entrepreneurship, innovation, and growth. *Managerial and Decision Economics* 35, pp. 67–72.

Klette, T.J. et al. 2000. Do subsidies to commercial R&D reduce market failures? Microeconometric evaluation studies. *Research Policy* 29, pp. 471–495.

Kline, R.B. 2011. *Principles and practice of structural equation modeling*. 3rd ed. New York: Guilford Press.

Klingebiel, R. and Adner, R. 2015. Real options logic revisited: the performance effects of alternative resource allocation regimes. *Academy of Management Journal* 58(1), pp. 221–241.

Klingebiel, R. and De Meyer, A. 2013. Becoming aware of the unknown: decision making during the implementation of a strategic initiative. *Organization Science* 24(1), pp. 133–153.

Klingebiel, R. and Rammer, C. 2014. Resource allocation strategy for innovation portfolio management. *Strategic Management Journal* 35, pp. 246–268.

Knockaert, M. et al. 2006. Do human capital and fund characteristics drive follow-up behaviour of early stage high-tech VCs? *International Journal of Technology Management* 34(1/2), pp. 7–27.

Kock, A. et al. 2015. How ideation portfolio management influences front-end success. *Journal of Product Innovation Management* 32(4), pp. 539–555.

Koen, P. et al. 2001. Providing clarity and a common language to the 'fuzzy front end'. *Research Technology Management* 44(2), pp. 46–55.

Kogut, B. 1991. Joint ventures and the option to expand and acquire. *Management Science* 37(1), pp. 19–33.

Kogut, B. and Kulatilaka, N. 1994a. Operating flexibility, global manufacturing, and the option value of a multinational network. *Management Science* 40(1), pp. 123–139.

Kogut, B. and Kulatilaka, N. 1994b. Options thinking and platform investments investing in opportunity. *California Management Review* 36(2), pp. 52–71.

Kogut, B. and Kulatilaka, N. 2001. Capabilities as real options. *Organization Science* 12(6), pp. 744–758.

Kogut, B. and Kulatilaka, N. 2004. Real options pricing and organizations: the contingent risks of extended theoretical domains. *Academy of Management Review* 29(1), pp. 102–110.

Kogut, B. and Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science* 3(3), pp. 383–397.

Kortum, S. and Lerner, J. 2000. Assessing the contribution of venture capital to innovation. *RAND Journal of Economics* 31(4), pp. 674–692.

Kraus, M.W. and Keltner, D. 2009. Signs of socioeconomic status: a thin-slicing approach. *Psychological Science* 20(1), pp. 99–106.

Krychowski, C. and Quelin, B. V. 2010. Real options and strategic investment decisions: can they be of use to scholars? *Academy of Management Perspectives* 24(2), pp. 65–78.

Kumar, M.V.S. 2005. The value from acquiring and divesting a joint-venture: a real options approach. *Strategic Management Journal* 25, pp. 321–331.

Lampel, J. and Shamsie, J. 2000. Critical push: strategies for creating momentum in the motion picture industry. *Journal of Management* 26(2), pp. 233–257.

Lange, D. et al. 2011. Organizational reputation: a review. *Journal of Management* 37(1), pp. 153–

184.

Lant, T.K. 1992. Aspiration level adaptation: an empirical exploration. *Management Science* 38(5), pp. 623–644.

Lant, T.K. et al. 1992. The role of managerial learning and interpretation in strategic persistence and reorientation: an empirical exploration. *Strategic Management Journal* 13(8), pp. 585–608.

Lawrence, A. 2013. Individual investors and financial disclosure. *Journal of Accounting and Economics* 56(1), pp. 130–147.

Lee, C. et al. 2001. Internal capabilities, external networks, and performance: a study on technology-based ventures. *Strategic Management Journal* 22(6–7), pp. 615–640.

Lee, N. et al. 2015. Access to finance for innovative SMEs since the financial crisis. *Research Policy* 44, pp. 370–380.

Lee, S.-H. et al. 2007. Bankruptcy law and entrepreneurship development: a real options perspective. *Academy of Management Review* 32(1), pp. 257–272.

Lehavy, R. et al. 2011. The effect of annual report readability on analyst following and the properties of their earnings forecasts. *Accounting Review* 86(3), pp. 1087–1115.

Leiblein, M.J. and Miller, D.J. 2003. An empirical examination of transaction- and firm-level influence on the vertical boundaries of the firm. *Strategic Management Journal* 24(9), pp. 839–859.

Leiponen, A. and Helfat, C.E. 2010. Innovation objectives, knowledge sources, and the benefits of breadth. *Strategic Management Journal* 31(2), pp. 224–236.

Leleux, B. and Surlemont, B. 2003. Public versus private venture capital: seeding or crowding out? A pan-European analysis. *Journal of Business Venturing* 18(1), pp. 81–104.

Leonard-Barton, D. 1992. Core capabilities and core rigidities: a paradox in managing new product development. *Strategic Management Journal* 13, pp. 111–125.

Lerner, J. 1994. Venture capitalists and the decision to go public. *Journal of Financial Economics* 35(3), pp. 293–316.

Lerner, J. 1995. Venture capitalists and the oversight of private firms. *Journal of Finance* 50(1), pp. 301–318.

Lerner, J. 1999. The government as venture capitalist: the long-run impact of the SBIR program. *Journal of Business* 72(3), pp. 285–318.

Lerner, J. 2002. When bureaucrats meet entrepreneurs: the design of effective ‘public venture capital’ programmes. *Economic Journal* 112(February), pp. 73–84.

Lerner, J. 2010. The future of public efforts to boost entrepreneurship and venture capital. *Small Business Economics* 35(3), pp. 255–264.

Lerner, J. and Kegler, C. 2001. Evaluating the Small Business Innovation Research program: a literature review. In: Wessner, C. ed. *The Small Business Innovation Research Program (SBIR): An Assessment of the Department of Defense Fast Track Initiative*. Washington; D.C.: National Academy Press, pp. 397–426.

Lester, R.H. et al. 2006. Initial public offering investor valuations: an examination of top management team prestige and environmental uncertainty. *Journal of Small Business Management* 44(1), pp. 1–26.

Levinthal, D.A. 1997. Adaptation on rugged landscapes. *Management Science* 43(7), pp. 934–950.

Levinthal, D.A. and March, J.G. 1993. The myopia of learning. *Strategic Management Journal* 14, pp. 95–112.

Levitas, E. and Chi, T. 2010. A look at the value creation effects of patenting and capital investment through a real options lens: the moderating role of uncertainty. *Strategic Entrepreneurship Journal* 4(1), pp. 212–233.

Levitas, E. and McFadyen, M.A. 2009. Managing liquidity in research-intensive firms: signaling and cash flow effects of patents and alliance activities. *Strategic Management Journal* 30(6), pp. 659–678.

Lewis, M.W. et al. 2002. Product development tensions: exploring contrasting styles of project management. *Academy of Management Journal* 45(3), pp. 546–564.

Lewis, M.W. and Grimes, A.J. 1999. Metatriangulation: building theory from multiple paradigms. *Academy of Management Review* 24(4), pp. 672–690.

Li, F. 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* 45(2–3), pp. 221–247.

Li, J. and Rugman, A.M. 2007. Real options and the theory of foreign direct investment. *International Business Review* 16(6), pp. 687–712.

Li, Y. et al. 2007. Real options: taking stock and looking ahead. *Advances in Strategic Management* 24, pp. 31–66.

Li, Y. 2008. Duration analysis of venture capital staging: a real options perspective. *Journal of Business Venturing* 23(5), pp. 497–512.

Li, Y. and Chi, T. 2013. Venture capitalists' decision to withdraw: the role of portfolio configuration from a real options lens. *Strategic Management Journal* 34(11), pp. 1351–1366.

Liebeskind, J.P. et al. 1996. Social networks, learning, and flexibility: sourcing scientific knowledge in new biotechnology firms. *Organization Science* 7(4), pp. 428–443.

Link, A.N. et al. 2014. Private equity and the innovation strategies of entrepreneurial firms: empirical evidence from the Small Business Innovation Research program. *Managerial and Decision Economics* 35(2), pp. 103–113.

Link, A.N. and Ruhm, C.J. 2009. Bringing science to market: commercializing from NIH SBIR awards. *Economics of Innovation and New Technology* 18(3–4), pp. 381–402.

Link, A.N. and Scott, J.T. 2009. Private investor participation and commercialization rates for government-sponsored research and development: would a prediction market improve the performance of the SBIR programme? *Economica* 76(302), pp. 264–281.

Link, A.N. and Scott, J.T. 2010. Government as entrepreneur: evaluating the commercialization success of SBIR projects. *Research Policy* 39(5), pp. 589–601.

Lint, O. and Pennings, E. 2001. An option approach to the new product development process: a case study at Philips Electronics. *R&D Management* 31(2), pp. 163–172.

Lippman, S.A. and Rumelt, R.P. 1982. Uncertain imitability: an analysis of interfirm differences in efficiency under competition. *The Bell Journal of Economics* 13(2), pp. 418–438.

Little, R.J.A. and Rubin, D.B. 2002. *Statistical analysis with missing data*. 2nd editio. Hoboken, New Jersey: John Wiley & Sons.

Liu, Q. and Wong, K.P. 2011. Intellectual capital and financing decisions: evidence from the us patent data. *Management Science* 57(10), pp. 1861–1878.

Loch, C.H. et al. 2008. Diagnosing unforeseeable uncertainty in a new venture. *Journal of Product Innovation Management* 25(1), pp. 28–46.

Loughran, T. and McDonald, B. 2014. Measuring readability in financial disclosures. *Journal of Finance* 69(4), pp. 1643–1671.

Low, M.B. and MacMillan, I.C. 1988. Entrepreneurship: past research and future challenges. *Journal of Management* 14, pp. 139–161.

Lowe, R.A. and Gonzalez-Brambila, C. 2007. Faculty entrepreneurs and research productivity. *Journal of Technology Transfer* 32(3), pp. 173–194.

Lu, J.W. and Beamish, P.W. 2004. International diversification and firm performance: the S-curve hypothesis. *Academy of Management Journal* 47(4), pp. 598–609.

Lu, Z.J. and Comanor, W.S. 1998. Strategic pricing of new pharmaceuticals. *Review of Economics and Statistics* 80(1), pp. 108–118.

Luehrman, T.A. 1998a. Investment opportunities as real options. *Harvard Business Review* 76(4), pp. 51–67.

Luehrman, T.A. 1998b. Strategy as a portfolio of real options. *Harvard Business Review* 76(5), pp. 89–99.

Luukkonen, T. et al. 2013. The value added by government venture capital funds compared with independent venture capital funds. *Technovation* 33(4–5), pp. 154–162.

Macmillan, I.C. et al. 1985. Criteria used by venture capitalists to evaluate new venture proposals. *Journal of Business Venturing* 1(1), pp. 119–128.

Macmillan, I.C. et al. 1987. Criteria distinguishing successful from unsuccessful ventures in the venture screening process. *Journal of Business Venturing* 2(2), pp. 123–137.

Macmillan, I.C. et al. 1989. Venture capitalists’ involvement in their investments: extent and performance. *Journal of Business Venturing* 4(1), pp. 27–47.

Mahmood, I.P. et al. 2011. Where can capabilities come from? Network ties and capability acquisition in business groups. *Strategic Management Journal* 32, pp. 820–848.

Mallows, C.L. 1986. Augmented partial residuals. *Technometrics* 28, pp. 313–319.

Manigart, S. et al. 2002. Determinants of required return in venture capital investments: a five-country study. *Journal of Business Venturing* 17(4), pp. 291–312.

March, J.G. 1991. Exploration and exploitation in organizational learning. *Organization Science* 2(1), pp. 71–87.

March, J.G. and Olsen, J.P. 1976. *Ambiguity and choice in organizations*. Bergen, Norway: Universitesforlaget.

March, J.G. and Simon, H.A. 1958. *Organizations*. Oxford, England: Wiley.

Markham, S.K. 2013. The impact of front-end innovation activities on product performance. *Journal of Product Innovation Management* 30(S1), pp. 77–92.

Markman, G.D. et al. 2008. Research and technology commercialization. *Journal of Management Studies* 45(8), p. 1401–1423Markman, G.D. et 2008. Research and t.

Martin, J.A. 2011. Dynamic managerial capabilities and the multibusiness team: the role of episodic teams in executive leadership groups. *Organization Science* 22(1), pp. 118–140.

McGrath, R.G. 1997. A real options logic for initiating technology positioning investments. *Academy of Management Review* 22(4), p. 974.

McGrath, R.G. 1999. Falling forward: real options reasoning and entrepreneurial failure. *Academy of Management Review* 24(1), pp. 13–30.

McGrath, R.G. et al. 2004. Real options as engines of choice and heterogeneity. *Academy of Management Review* 29(1), pp. 86–101.

McGrath, R.G. and MacMillan, I.C. 2000. Assessing technology projects using real options reasoning. *Research Technology Management* 43(4), pp. 35–49.

McGrath, R.G. and Nerkar, A. 2004. Real options reasoning and a new look at the R&D investment strategies of pharmaceutical firms. *Strategic Management Journal* 25(1), pp. 1–21.

McLaughlin, G.H. 1969. SMOG grading: a new readability formula. *Journal of Reading* 12(8), pp. 639–646.

McMillan, S.G. et al. 1995. Firm management of scientific information: some predictors and implications of openness versus secrecy. *R&D Management* 25(4), pp. 411–419.

McMillan, S.G. et al. 2003. The impact of publishing and patenting activities on new product development and firm performance: the case of the US pharmaceutical industry. *International Journal of Innovation Management* 7(2), pp. 213–221.

McNamara, G.M. et al. 2008. The performance implications of participating in an acquisition wave: early mover advantages, bandwagon effects, and the moderating influence of industry characteristics and acquirer tactics. *Academy of Management Journal* 51(1), pp. 113–130.

Meeusen, W. and Van Den Broeck, J. 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review* 18(2), pp. 435–444.

Megginson, W.L. and Weiss, K.A. 1991. Venture capitalist certification in initial public offerings. *Journal of Finance* 46(3), pp. 879–903.

De Meza, D. 2002. Overlending? *Economic Journal* 112(477), pp. F17–F31.

Mikkelson, W.H. et al. 1997. Ownership and operating performance of companies that go public. *Journal of Financial Economics* 44(3), pp. 281–307.

Miller, D. 1993. The Architecture of simplicity. *Academy of Management Review* 18(1), pp. 116–138.

Miller, D. and Shamsie, J. 2001. Learning across the life cycle: experimentation and performance among the Hollywood studio heads. *Strategic Management Journal* 22(8), pp. 725–745.

Miller, K.D. and Arikan, A.T. 2004. Technology search investments: evolutionary, option reasoning, and option pricing approaches. *Strategic Management Journal* 25(5), pp. 473–485.

Miller, K.D. and Shapira, Z. 2004. An empirical test of heuristics and biases affecting real option valuation. *Strategic Management Journal* 25(3), pp. 269–284.

Miller, K.D. and Waller, H.G. 2003. Scenarios, real options and integrated risk management. *Long Range Planning* 36(1), pp. 93–107.

Miller, T. and Triana, M. del C. 2009. Demographic diversity in the boardroom: mediators of the board diversity–firm performance relationship. *Journal of Management Studies* 46(5), pp. 755–786.

Minola, T. and Giorgino, M. 2008. Who's going to provide the funding for high tech start-ups? A model for the analysis of determinants with a fuzzy approach. *R&D Management* 38(3), pp. 335–351.

Mintz, O. and Currim, I.S. 2013. What drives managerial use of marketing and financial metrics and does metric use affect performance of marketing-mix activities? *Journal of Marketing* 77(March), pp. 17–40.

Modigliani, F. and Miller, M.H. 1958. The cost of capital, corporation finance and the theory of investment. *American Economic Review* 48(3), pp. 261–297.

Moel, A. and Tufano, P. 2002. When are real options exercised? An empirical study of mine closings. *Review of Financial Studies* 15(1), pp. 35–64.

Morgan, N.A. and Rego, L.L. 2009. Brand portfolio strategy and firm performance. *Journal of Marketing* 73(January), pp. 59–74.

Morris, R.D. 1987. Signalling, Agency Theory and Accounting Policy Choice. *Accounting and Business Research* 18(69), pp. 47–56.

Mosey, S. and Wright, M. 2007. From human capital to social capital: a longitudinal study of technology-based academic entrepreneurs. *Entrepreneurship Theory and Practice* 31(6), pp. 909–935.

Moss, T.W. et al. 2015. The effect of virtuous and entrepreneurial orientations on microfinance lending and repayment: a signaling theory perspective. *Entrepreneurship Theory and Practice* January, pp. 27–52.

Mossholder, K.W. and Bedeian, A.G. 1983. Cross-level inference and organizational research: perspectives on interpretation and application. *Academy of Management Review* 8, pp. 547–558.

Mosteller, F. and Tukey, J.W. 1977. *Data analysis and regression*. Reading, MA: Addison-Wesley.

Munari, F. and Toschi, L. 2015. Assessing the impact of public venture capital programmes in the United Kingdom: do regional characteristics matter? *Journal of Business Venturing* 30(2), pp. 205–226.

Murphy, G.B. et al. 1996. Measuring performance in entrepreneurship research. *Journal of Business Research* 36(1), pp. 15–23.

Murray, F.E. 2004. The role of academic inventors in entrepreneurial firms: sharing the laboratory life. *Research Policy* 33(4), pp. 643–659.

Myers, S.C. and Majluf, N.S. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13(2), pp. 187–221.

Nahapiet, J. and Ghoshal, S. 1998. Social capital, intellectual capital and the organizational advantage. *Academy of Management Review* 23(2), pp. 242–266.

Nanda, R. et al. 2015. Innovation and entrepreneurship in renewable energy. In: Jaffe, A. and Jones, B. eds. *The Changing Frontier: Rethinking Science and Innovation Policy*. National Bureau of Economic Research.

Nanda, R. and Rhodes-Kropf, M. 2016. Financing risk and innovation. *Management Science* (Articles in Advance), pp. 1–19.

Narasimhan, O. et al. 2006. Absorptive capacity in high-technology markets: the competitive advantage of the haves. *Marketing Science* 25(5), pp. 510–524.

Ndofor, H.A. and Levitas, E. 2004. Signaling the strategic value of knowledge. *Journal of Management* 30(5), pp. 685–702.

Negro, G. et al. 2014. Category signaling and reputation. *Organization Science* 26(2), pp. 584–600.

Neher, D. V. 1999. Staged financing: an agency perspective. *Review of Economic Studies* 66(2), pp. 255–274.

Nelson, R.R. 1959. The simple economics of basic scientific research. *Journal of Political Economy* 67(3), pp. 297–306.

Nelson, R.R. and Winter, S.G. 1982. *An evolutionary theory of economic change*. Cambridge, MA: Harvard University Press.

Nerkar, A. 2003. Old is gold? The value of temporal exploration in the creation of new knowledge. *Management Science* 49(2), pp. 211–229.

Newbert, S.L. 2008. Value, rareness, competitive advantage, and performance: a conceptual-level empirical investigation of the resource-based view of the firm. *Strategic Management Journal* 29(7), pp. 745–768.

Newton, D.P. et al. 2004. Real R&D options. *International Journal of Management Reviews* 5(2), pp. 113–130.

Nicolaou, N. and Souitaris, V. 2016. Can perceived support for entrepreneurship keep great faculty in the face of spinouts? *Journal of Product Innovation Management* 33(3), pp. 298–319.

NIH 2015. About NIH | National Institutes of Health (NIH) [Online] Available at: http://www.nih.gov/about-nih [Accessed: 6 November 2015].

O'Brien, J. and Folta, T.B. 2009. Sunk costs, uncertainty and market exit: a real options perspective. *Industrial and Corporate Change* 18(5), pp. 807–833.

O'Brien, J.P. et al. 2003. A real options perspective on entrepreneurial entry in the face of uncertainty. *Managerial and Decision Economics* 24(8), pp. 515–533.

O'Shea, M. and Stevens, C. 1998. Governments as venture capitalists. *The OECD Observer* (213), pp. 26–29.

Ocasio, W. 1997. Towards an attention-based view of the firm. *Strategic Management Journal* 18(Summer Special Issue), pp. 187–206.

OECD 1997. *Government venture capital for technology-based firms*. Paris. OECD Publishing.

OECD 2015a. *Entrepreneurship at a glance 2015*. Paris. OECD Publishing.

OECD 2015b. *OECD science, technology and industry scoreboard 2015: innovation for growth and society*. Paris. OECD Publishing.

Van Osnabrugge, M. and Robinson, R.J. 2000. *Angel investing: matching startup funds with startup companies: the guide for entrepreneurs and individual investors, and venture capitalists*. 1st ed. San Francisco: Jossy Bass, A Wiley Company.

Pantzalis, C. 2001. Does location matter? An empirical analysis of geographic scope and MNC market valuation. *Journal of International Business Studies* 32(1), pp. 133–155.

Patel, P.C. and Jayaram, J. 2014. The antecedents and consequences of product variety in new ventures: an empirical study. *Journal of Operations Management* 32(1–2), pp. 34–50.

Patricof, A. 1989. The internationalisation of venture capital. *Journal of Business Venturing* 4, pp.

227–230.

Patzelt, H. et al. 2009. Upper echelons and portfolio strategies of venture capital firms. *Journal of Business Venturing* 24(6), pp. 558–572.

Pavitt, K. 1998. The inevitable limits of EU R&D funding. *Research Policy* 27(6), pp. 559–568.

Paxson, D.A. 2003. *Real R&D options*. Oxford: Butterworth-Heinemann.

Payne, G.T. et al. 2013. Signaling organizational virtue: an examination of virtue rhetoric, country-level corruption, and performance of foreign IPOs from emerging and developed economies. *Strategic Entrepreneurship Journal* 7(3), pp. 230–251.

Payne, J.W. et al. 1988. Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition* 14(3), pp. 534–552.

Peters, F.S. and Wagner, A.F. 2014. The executive turnover risk premium. *Journal of Finance* 69(4), pp. 1529–1563.

Pettigrew, A. 1990. Longitudinal field research on change: theory and practice. *Organization Studies* 1(3), pp. 267–291.

Pich, M.T. et al. 2002. On uncertainty, ambiguity, and complexity in project management. *Management Science* 48(8), pp. 1008–1023.

Picot, G. and Dupuy, R. 1998. Job creation by company size class: the magnitude, concentration and persistence of job gains and losses in Canada. *Small Business Economics* 10, pp. 117–139.

Pisano, G.P. 1994. Knowledge, integration, and the locus of learning: an empirical analysis of process development. *Strategic management journal* 15, pp. 85–100.

Podolny, J.M. 2001. Networks as the pipes and prisms of the market. *American Journal of Sociology* 107(1), pp. 33–60.

Podolny, J.M. and Phillips, D.J. 1996. The dynamics of organizational status. *Industrial and Corporate Change* 5(2), pp. 453–471.

Politis, D. 2005. The process of entrepreneurial learning: a conceptual framework. *Entrepreneurship Theory and Practice* 29(4), pp. 399–424.

Powell, T.C. 2001. Competitive advantage: logical and philosophical considerations. *Strategic Management Journal* 22(9), pp. 875–888.

Powell, W.W. and Owen-Smith, J. 1998. Universities and the market for intellectual property in the life sciences. *Journal of Policy Analysis and Management* 17(2), pp. 253–277.

Prabhu, J.C. et al. 2005. The impact of acquisitions on innovation: poison pill, placebo, or tonic? *Journal of Marketing* 69(January), pp. 114–130.

Prahalad, C.K. and Hamel, G. 1990. The core competence of the corporation. *Harvard Business Review* (May-June), pp. 1–15.

Priem, R.L. and Butler, J.E. 2001. Tautology in the resource-based view and the implications of externally determined resource value: further comments. *Academy of Management Review* 26(1), pp. 57–66.

Puri, M. and Zarutskie, R. 2012. On the life cycle dynamics of venture-capital- and non-venture-capital-financed firms. *Journal of Finance* 67(6), pp. 2247–2293.

Qian, H. and Acs, Z.J. 2013. An absorptive capacity theory of knowledge spillover entrepreneurship.

Small Business Economics 40(2), pp. 185–197.

Ramani, S. V. et al. 2008. On estimating a knowledge production function at the firm and sector level using patent statistics. *Research Policy* 37(9), pp. 1568–1578.

Ramaswami, A. et al. 2010. Gender, mentoring, and career success: the importance of organizational context. *Personnel Psychology* 63(2), pp. 385–405.

Ray, G. et al. 2004. Capabilities, business processes, and competitive advantage: choosing the dependent variable in empirical tests of the resource-based view. *Strategic Management Journal* 25(1), pp. 23–37.

ReadabilityScore 2015. Free Online Readability Calculator - Flesch Kincaid, Gunning Fog and more [Online] Available at: https://readability-score.com/ [Accessed: 12 November 2015].

Reed, K.K. et al. 2006. Proposing and testing an intellectual capital-based view of the firm. *Journal of Management Studies* 43(4), pp. 867–893.

Reed, R. and DeFillippi, R.J. 1990. Causal ambiguity, barriers to imitation, and sustainable competitive advantage. *Academy of Management Review* 15(1), pp. 88–102.

Rego, L.L. et al. 2013. Reexamining the market share-customer satisfaction relationship. *Journal of Marketing* 77(September), pp. 1–20.

Remenyi, D. et al. 1998. *Doing research in business and management: an introduction to process and method*. London: Sage Publications.

Reuer, J.J. and Leiblein, M.J. 2000. Downside risk implications of multinationality and international joint ventures. *Academy of Management Journal* 43(2), pp. 203–214.

Reuer, J.J. and Tong, T.W. 2007. How do real options matter? Empirical research on strategic investments and firm performance. *Advances in strategic management* 24(716), pp. 145–173.

Reyt, J.-N. and Wiesenfeld, B.M. 2015. Seeing the forest for the trees: exploratory learning, mobile technology, and knowledge workers' role integration behaviors. *Academy of Management Journal* 58(3), pp. 739–762.

Riley, J.G. 2001. Silver signals: twenty-five years of screening and signaling. *Journal of Economic Literature* 39(2), pp. 432–478.

Da Rin, M. et al. 2013. A survey of venture capital research. In: Constantinides, G. et al. eds. *Handbook of the Economics of Finance, Volume 2, Part A*. Amsterdam: North Holland, pp. 573–648.

Roberts, E.B. 1991. High stakes for high-tech entrepreneurs: understanding venture capital decision making. *MIT Sloan Management Review* 32(2), pp. 9–20.

Romer, P.M. 1990. Endogenous technological change. *Journal of Political Economy* 98(5), pp. 71–102.

Rosenkopf, L. and Nerkar, A. 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal* 22(4), pp. 287–306.

Rousseau, D.M. 1985. Issues of level in organizational research: multi-level and cross-level perspectives. *Research in Organizational Behavior* 7, pp. 1–37.

Rubin, D.B. 1976. Inference and missing data. *Biometrika* 63(3), p. 581.

Sahlman, W.A. 1990. The structure and governance of venture-capital organizations. *Journal of Financial Economics* 27(2), pp. 473–521.

Samila, S. and Sorenson, O. 2011. Venture capital, entrepreneurship, and economic growth. *Review of Economics and Statistics* 93(1), pp. 338–349.

Sanchez, R. 1993. Strategic flexibility, firm organization, and managerial work in dynamic markets: a strategic options perspective. *Advances in Strategic Management* 9(1), pp. 251–291.

Sanders, G.W.M. and Boivie, S. 2004. Sorting things out: valuation of new firms in uncertain markets. *Strategic Management Journal* 25(2), pp. 167–186.

Sanders, G.W.M. and Carpenter, M.A. 1998. Internationalization and firm governance: the roles of CEO compensation, top team composition, and board structure. *Academy of Management Journal* 41(2), pp. 158–178.

Sapienza, H.J. and Gupta, A.K. 1994. Impact of agency risks and task uncertainty on venture capitalist-CEO interaction. *Academy of Management Journal* 37(6), pp. 1618–1632.

Sauer, S.J. et al. 2010. Too good to be true? The unintended signaling effects of educational prestige on external expectations of team performance. *Organization Science* 21(5), pp. 1108–1120.

Saunders, M. et al. 2012. *Research methods for business students*. Pearson Education.

SBIR 2015. About | SBIR.gov [Online] Available at: https://www.sbir.gov/about [Accessed: 6 November 2015].

Schafer, J.L. 1997. *Analysis of incomplete multivariate data*. Boca Raton, Florida: Chapman & Hall/CRC.

Schafer, J.L. and Graham, J.W. 2002. Missing data: our view of the state of the art. *Psychological Methods* 7(2), pp. 147–177.

Scheingberg, S. and MacMillan, I.C. 1988. An 11 country study of the motivations to start a business. In: Kirchhoff, B. A. et al. eds. *Frontiers of Entrepreneurship Research*. Wellesley, MA: Babson College, pp. 669–687.

Scherpereel, C.M. 2008. The option-creating institution: a real options perspective on economic organization. *Strategic Management Journal* 29(5), pp. 455–470.

Schmidt, J.B. et al. 2009. Exploring new product development project review practices. *Journal of Product Innovation Management* 26(5), pp. 520–535.

Schumpeter, J. 1942. *Capitalism, socialism, and democracy*. New York: Harper.

Scott, J.T. 2000. The directions for technological change: alternative economic majorities and opportunity costs. *Review of Industrial Organization* 17(1), pp. 1–16.

Semadeni, M. et al. 2014. The perils of endogeneity and instrumental variables in strategy research: understanding through simulations. *Strategic Management Journal* 35, pp. 1070–1079.

Shane, S. and Stuart, T.E. 2002. Organizational endowments and the performance of university start-ups. *Management Science* 48(1), pp. 154–170.

Shanghairanking 2013. Academic Ranking of World Universities - 2013 | Top 500 universities | Shanghai Ranking - 2013 [Online] Available at: http://www.shanghairanking.com/ARWU2013.html [Accessed: 13 November 2015].

Sharp, D.J. 1991. Uncovering the hidden value in high-risk investments. *MIT Sloan Management Review* 32(4), pp. 69–74.

Shaver, J.M. 1998. Accounting for endogeneity when assessing strategy performance: does entry mode choice affect FDI survival? *Management Science* 44(4), pp. 571–585.

Shepherd, D.A. 1999. Venture capitalists' introspection: a comparison of 'in use' and 'espoused' decision policies. *Journal of Small Business Management* 27, pp. 76–87.

Shiffrin, R.M. and Schneider, W. 1977. Controlled and automatic human information processing: II. Perceptual learning, automatic attending and a general theory. *Psychological Review* 84(2), pp. 127–190.

Shrader, R.C. and Simon, M. 1997. Corporate versus independent new ventures: resource, strategy, and performance differences. *Journal of Business Venturing* 12(1), pp. 47–66.

Siegel, D.S. et al. 2007. Technology transfer offices and commercialization of university intellectual property: performance and policy implications. *Oxford Review of Economic Policy* 23(4), pp. 640–660.

Simar, L. and Wilson, P.W. 1998. Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Management Science* 44(1), pp. 49–61.

Simar, L. and Wilson, P.W. 2008. Statistical inference in nonparametric frontier models: recent developments and perspectives. In: Fried, H. O. et al. eds. *The Measurement of Productive Efficiency and Productivity Growth*. New York: Oxford University Press, pp. 421–521.

Simon, H.A. 1947. *Administrative behavior: a study of decision-making processes in administrative organizations*. Chicago, IL: Macmillan.

Simon, H.A. 1983. *Reason in human affairs*. Oxford: Basil Blackwell.

Simon, H.A. 1991. Bounded rationality and organizational learning. *Organization science* 2(1), pp. 125–135.

Sine, W.D. et al. 2006. Revisiting burns and stalker: Formal structure and new venture performance in emerging economic sectors. *Academy of Management Journal* 49(1), pp. 121–132.

Singh, J. and Fleming, L. 2010. Lone inventors as sources of breakthroughs: myth or reality? *Management Science* 56(1), pp. 41–56.

Slater, S.F. et al. 1998. Evaluating strategic investments: complementing discounted cash flow analysis with options analysis. *Industrial Marketing Management* 27(5), pp. 447–458.

Snedecor, G.W. and Cochran, W.G. 1967. *Statistical methods*. 6th ed. Ames, Iowa: Iowa State University Press.

Snijders, T.A.B. 2005. Power and sample size in multilevel modeling. In: Everitt, B. S. and Howell, D. C. eds. *Encyclopedia of Statistics in Behavioral Science*. Chicester: Wiley, pp. 1570–1573.

Sobel, R.S. 2008. Testing Baumol: institutional quality and the productivity of entrepreneurship. *Journal of Business Venturing* 23(6), pp. 641–655.

Solow, R.M. 1957. Technical change and the aggregate production function. *Review of Economics and Statistics* 39(3), pp. 312–320.

Sommer, S.C. et al. 2009. Managing complexity and unforeseeable uncertainty in startup companies: an empirical study. *Organization Science* 20(1), pp. 118–133.

Sommer, S.C. and Loch, C.H. 2004. Selectionism and learning in projects with complexity and unforeseeable uncertainty. *Management Science* 50(10), pp. 1334–1347.

Sorenson, O. 2000. Letting the market work for you: an evolutionary perspective on product strategy. *Strategic Management Journal* 21(5), pp. 577–592.

Sorescu, A.B. et al. 2003. Sources and financial consequences of radical innovation: insights from pharmaceuticals radical. *Journal of Marketing* 67(October), pp. 82–102.

Sosa, M.L. 2009. Application-specific R&D capabilities and the advantage of incumbents: evidence from the anticancer drug market. *Management Science* 55(8), pp. 1409–1422.

Spence, M. 1973. Job market signaling. *Quarterly Journal of Economics*, pp. 355–374.

Spence, M. 1974. Competitive and optimal responses to signals: an analysis of efficiency and distribution. *Journal of Economic Theory* 7(3), pp. 296–332.

Spence, M. 2002. Signaling in retrospect and the informational structure of markets. *American Economic Review* 92(3), pp. 434–459.

Stamp, G. 1981. Levels and types of managerial capability. *Journal of Management Studies* 18(3), pp. 277–297.

Starr, J.A. and Macmillan, I.C. 1990. Resource cooptation via social contracting: resource acquisition strategies for new ventures. *Strategic Management Journal* 11, pp. 79–92.

StataCorp 2013. *Stata 13 base reference manual*. College Station, TX: Stata Press.

Staw, B.M. et al. 1981. Threat-rigidity effects in organizational behavior: a multilevel analysis. *Administrative Science Quarterly* 26, pp. 501–524.

Stel, A. Van et al. 2005. The effect of entrepreneurial activity on national economic growth. *Small Business Economics* 24(3), pp. 311–321.

Stern, I. et al. 2008. Unmixed signals: how reputation and status affect alliance formation. *Academy of Management Journal* 35, pp. 512–531.

Stiglitz, J.E. 2000. The contributions of the economics of information to twentieth century economics. *Quarterly Journal of Economics* 115, pp. 1441–1478.

Stinchcombe, A.L. 1968. *Constructing social theories*. Chicago, IL: Chicago University Press.

Stuart, T.E. et al. 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative Science Quarterly* 44(2), pp. 315–349.

Su, M. and Rao, V.R. 2010. New product preannouncement as a signaling strategy: an audience-specific review and analysis. *Journal of Product Innovation Management* 27(5), pp. 658–672.

Subramaniam, M. and Youndt, M.A. 2005. The influence of intellectual capital on the types of innovative capabilities. *Academy of Management Journal* 48(3), pp. 450–463.

Suchman, M.C. 1995. Managing legitimacy: strategic and institutional approaches. *Academy of Management Review* 20(3), pp. 571–610.

Sull, D.N. 2003. Managing by commitments. *Harvard Business Review* 81(6), pp. 82–91.

Taylor, A. and Greve, H.R. 2006. Superman or the fantastic four? Knowledge combination and experience in innovative teams. *Academy of Management Journal* 49(4), pp. 723–740.

Teece, D.J. 1986. Profiting from technological innovation. *Research Policy* 15, pp. 285–305.

Teece, D.J. et al. 1997. Dynamic capabilities and strategic management. *Strategic Management Journal* 18(7), pp. 509–533.

Teece, D.J. 1998. Capturing value from knowledge assets: the new economy, markets for know-how, and intangible assets. *California Management Review* 40(3), pp. 55–79.

Teece, D.J. 2012. Dynamic capabilities: routines versus entrepreneurial action. *Journal of Management Studies* 49(8), pp. 1395–1401.

Thompson, J.D. 1967. *Organizations in action*. New York: McGraw- Hil.

Thorpe, R. et al. 2005. Using knowledge within small and medium-sized firms: a systematic review of the evidence. *International Journal of Management Reviews* 7(4), pp. 257–281.

Thursby, J.G. and Thursby, M.C. 2002. Who is selling the ivory tower? Sources of growth in university licensing. *Management Science* 48(1), pp. 90–104.

Tihanyi, L. et al. 2000. Composition of the top management team and firm international diversification. *Journal of Management* 26(6), pp. 1157–1177.

Tirole, J. 1996. A theory of collective reputations (with applications to the persistence of corruption and to firm quality). *Review of Economic Studies* 63(1), pp. 1–22.

Tong, T.W. et al. 2008. International joint ventures and the value of growth options. *Academy of Management Journal* 51(5), pp. 1014–1029.

Tong, T.W. and Reuer, J.J. 2006. Firm and industry influences on the value of growth options. *Strategic Organization* 4(1), pp. 71–95.

Toole, A.A. and Czarnitzki, D. 2007. Biomedical academic entrepreneurship through the SBIR program. *Journal of Economic Behavior and Organization* 63(4), pp. 716–738.

Toole, A.A. and Czarnitzki, D. 2009. Exploring the relationship between scientist human capital and firm performance: the case of biomedical academic entrepreneurs in the SBIR program. *Management Science* 55(1), pp. 101–114.

Toole, A.A. and Czarnitzki, D. 2010. Commercializing science: is there a university ‘brain drain’ from academic entrepreneurship? *Management Science* 56(9), pp. 1599–1614.

Tornikoski, E.T. and Newbert, S.L. 2007. Exploring the determinants of organizational emergence: a legitimacy perspective. *Journal of Business Venturing* 22(2), pp. 311–335.

Trajtenberg, M. 1990. A penny for your quotes: patent citations and the value of innovations. *RAND Journal of Economics* 21(1), pp. 172–187.

Triantis, A. 2005. Realizing the potential of real options: does theory meet practice? *Journal of Applied Corporate Finance* 17(2), pp. 8–16.

Trigeorgis, L. 1993. The nature of option interactions and the valuation of investments with multiple real options. *Journal of Financial and Quantitative Analysis* 28(1), pp. 1–20.

Trigeorgis, L. 1996. *Real options: managerial flexibility and strategy in resource allocation*. Cambridge, MA: MIT Press.

Trigeorgis, L. 2005. Making use of real options simple: an overview and applications in flexible/modular decision making. *Engineering Economist* 50(1), pp. 25–53.

Turner, J.R. et al. 2009. Project management in small to medium-sized enterprises: a comparison between firms by size and industry. *International Journal of Managing Projects in Business* 2(2), pp. 282–296.

Tushman, M.L. 1977. Special boundary roles in the innovation process. *Administrative Science*

Quarterly 22(4), pp. 587–605.

Tushman, M.L. and Anderson, P. 1986. Technological discontinuities and organizational environments. *Administrative Science Quarterly* 31(3), pp. 439–465.

Tversky, A. and Kahneman, D. 1974. Judgment under uncertainty: heuristics and biases. *Science* 185(4157), pp. 1124–1131.

Tyebjee, T.T.T. and Bruno, A. V. 1984. A model of venture capitalist investment activity. *Management Science* 30(9), pp. 1051–1066.

Ucbasaran, D. et al. 2009. The extent and nature of opportunity identification by experienced entrepreneurs. *Journal of Business Venturing* 24(2), pp. 99–115.

Unger, J.M. et al. 2011. Human capital and entrepreneurial success: a meta-analytical review. *Journal of Business Venturing* 26(3), pp. 341–358.

Urbig, D. et al. 2013. Investor reactions to new product development failures: the moderating role of product development stage. *Journal of Management* 39(4), pp. 985–1015.

Vassolo, R.S. et al. 2004. Non-additivity in portfolios of exploration activities: a real options-based analysis of equity alliances in biotechnology. *Strategic Management Journal* 25(11), pp. 1045–1061.

De Vaus, D. 2001. *Research design in social research*. Sage Publications.

Verona, G. 1999. A resource-based view of product development. *Academy of Management Review* 24(1), pp. 132–142.

Vorhies, D.W. et al. 2009. Product-market strategy and the marketing capabilities of the firm: impact of market effectiveness and cash flow performance. *Strategic Management Journal* 30(12), pp. 1310–1334.

Vorhies, D.W. et al. 2010. Improving customer-focused marketing capabilities and firm financial performance via marketing exploration and exploitation. *Journal of the Academy of Marketing Science* 39(5), pp. 736–756.

Voss, G.B. and Voss, Z.G. 2013. Strategic ambidexterity in small and medium-sized enterprises: implementing exploration and exploitation in product and market domains. *Organization Science* 24(5), pp. 1459–1477.

Vural, O.M. et al. 2013. Collaborative benefits and coordination costs: learning and capability development in science. *Strategic Entrepreneurship Journal* 7, pp. 122–137.

Wallsten, S. 2000. The effects of government-industry R&D programs on private R&D: the case of the Small Business Innovation Research Program. *RAND Journal of Economics* 31, pp. 82–100.

Walske, J.M. and Zacharakis, A.L. 2009. Genetically engineered: why some venture capital firms are more successful than others. *Entrepreneurship Theory and Practice* (January), pp. 297–319.

Wang, H.C. et al. 2009. Firm-specific knowledge resources and competitive advantage: the roles of economic- and relationship-based employee governance mechanisms. *Strategic Management Journal* 30, pp. 1265–1285.

Wang, R. et al. 1992. Secondary data analysis when there are missing observations. *Journal of the American Statistical Association* 57(4207454), pp. 952–961.

Wang, S. and Zhou, H. 2004. Staged financing in venture capital: moral hazard and risks. *Journal of Corporate Finance* 10(1), pp. 131–155.

Wang, T. et al. 2014. Legitimacy and the value of early customers. *Journal of Product Innovation Management* 31(5), pp. 1057–1075.

Warner, A.G. et al. 2006. Managing uncertainty in a formal standards-based industry: a real options perspective on acquisition timing. *Journal of Management* 32(2), pp. 279–298.

Weiss, A. 1995. Human capital vs. signalling explanations of wages. *Journal of Economic Perspectives* 9(4), pp. 133–154.

Wennberg, K. et al. 2011. The effectiveness of university knowledge spillovers: performance differences between university spinoffs and corporate spinoffs. *Research Policy* 40(8), pp. 1128–1143.

Wennekers, S. and Thurik, R. 1999. Linking entrepreneurship and economic growth. *Small business economics* 13, pp. 27–55.

Wernerfelt, B. 1984. A resource-based view of the firm. *Strategic Management Journal* 5(2), pp. 171–180.

Wetherill, G.B. 1986. *Regression analysis with applications*. London: Chapman & Hall.

Wiersema, M.F. and Bantel, K.A. 1992. Top management team demography and corporate strategic change. *Academy of Management Journal* 35(1), pp. 91–121.

Winter, S.G. 1971. Satisficing, selection, and the innovating remnant. *Quarterly Journal of Economics* 85(2), pp. 237–261.

Wooldridge, J.M. 2010. *Econometric analysis of cross section and panel data*. 2nd ed. Cambridge, Massachusetts: The MIT Press.

Wright, M. et al. 2005. International venture capital research: from cross country comparisons to crossing borders. *International Journal of Management Reviews* 7(3), pp. 135–165.

Wright, M. and Robbie, K. 1998. Venture capital and private equity: a review and synthesis. *Journal of Business Finance & Accounting* 25(5/6), pp. 521–570.

Wu, S. et al. 2005. CEO tenure and company invention under differing levels of technological dynamism. *Academy of Management Journal* 48(5), pp. 859–873.

Xiong, G. and Bharadwaj, S.G. 2011. Social capital of young technology firms and their IPO values: the complementary role of relevant absorptive capacity. *Journal of Marketing* 75(November), pp. 87–104.

Yeoh, P.-L. and Roth, K. 1999. An empirical analysis of sustained advantage in the U.S. pharmaceutical industry: impact of firm resources and capabilities. *Strategic Management Journal* 20(7), pp. 637–653.

Youndt, M.A. et al. 2004. Intellectual capital profiles: an examination of investments and returns. *Journal of Management Studies* 41(2), pp. 335–361.

Zacharakis, A.L. and Shepherd, D.A. 2001. The nature of information and overconfidence on venture capitalists' decision making. *Journal of Business Venturing* 16(4), pp. 311–332.

Zahra, S.A. et al. 2006. Entrepreneurship and dynamic capabilities: a review, model and research agenda. *Journal of Management Studies* 43(June), pp. 917–955.

Zahra, S.A. and Filatotchev, I. 2004. Governance of the entrepreneurial threshold firm: a knowledge-based perspective. *Journal of Management Studies* 41(5), pp. 885–897.

Zellner, A. 1962. An efficient method of estimating seemingly unrelated regression and test for aggregation bias. *Journal of the American Association* 57(298), pp. 348–368.

Zerbinati, S. et al. 2012. Nurture or nature? The growth paradox of research-based spin-offs. *Technology Analysis & Strategic Management* 24(1), pp. 21–35.

Zerbinati, S. and Souitaris, V. 2005. Entrepreneurship in the public sector: a framework of analysis in European local governments. *Entrepreneurship and Regional Development* 17(January), pp. 43–64.

Zhang, Y. 2006. The presence of a separate COO/president and its impact on strategic change and CEO dismissal. *Strategic Management Journal* 27(3), pp. 283–300.

Zhang, Y. and Wiersema, M.F. 2009. Stock market reaction to CEO certification: the signaling role of CEO background. *Strategic Management Journal* 30, pp. 693–710.

Zhao, Y.L. et al. 2013. Founding team capabilities and new venture performance: the mediating role of strategic positional advantages. *Entrepreneurship Theory and Practice* 37(4), pp. 789–814.

Zimmerman, M.A. 2008. The influence of top management team heterogeneity on the capital raised through an initial public offering. *Entrepreneurship Theory and Practice* (May), pp. 391–415.

Zimmerman, M.A. and Zeitz, G.J. 2002. Beyond survival: new achieving venture growth by building legitimacy. *Academy of Management Review* 27(3), pp. 414–431.

Zollo, M. and Singh, H. 2004. Deliberate learning in corporate acquisitions: Post-acquisition strategies and integration capability in U.S. bank mergers. *Strategic Management Journal* 25(13), pp. 1233–1256.

Zollo, M. and Winter, S.G. 2002. Deliberate learning and the evolution of dynamic capabilities. *Organization Science* 13(3), pp. 339–351.

Zott, C. 2003. Dynamic capabilities and the emergence of intraindustry differential firm performance: insights from a simulation study. *Strategic Management Journal* 24(2), pp. 97–125.

Zucker, L.G. et al. 1998. Intellectual human capital and the birth of U.S. biotechnology enterprises. *American Economic Review* 88(1), pp. 290–306.

Zucker, L.G. et al. 2002. Commercializing knowledge: university science, knowledge capture, and firm performance in biotechnology. *Management Science* 48(1), pp. 138–153.

Zwikael, O. and Smyrk, J. 2012. A general framework for gauging the performance of initiatives to enhance organizational value. *British Journal of Management* 23, pp. S6–S22.

Appendices

Appendix 1: National funding programmes in Europe

Source: Eurostars Report

Appendix 2: Standard ethical approval form

SURNAME: Scedrova

ETHICS 1

STANDARD ETHICAL APPROVAL FORM

Cardiff Business School
Cardiff University

Ysgol Fusnes Caerdydd
Prifysgol Caerdydd

This form should be completed for every research project that involves human participants. It can also be used to identify whether a full application for ethics approval needs to be submitted. The researcher or, where the researcher is a student, the supervisor, is responsible for exercising appropriate professional judgement in this review. This checklist must be completed before potential participants are approached to take part in any research.

APPLICATION APPROVED
Research Ethics Committee
Cardiff Business School
Cardiff University

SECTION 1 - RESEARCH CHECKLIST

1.1	**Does the study involve holding personal information (names, attributable information or personal identifiers of any form) on a database?**	YES/NO
1.2	**Does the study involve participants who are particularly vulnerable or unable to give free and informed consent (children, people with learning disabilities, students in academically dependent relationships)?**	YES/NO
1.3	**Will it be necessary for participants to take part in the study without their full knowledge and explicit consent (perhaps through covert observation)?**	YES/NO
1.4	**Will the study involve discussion of sensitive topics (political or religious views, illegal activities, sexual activity, drug use and so forth) that could be uncomfortable to participants or harmful if divulged to others?**	YES/NO
1.5	**Will the study involve potentially harmful procedures of any kind or be conducted in a hazardous environment that could expose the researchers or participants to higher risk than is encountered in normal life? http://www.cf.ac.uk/osheu/index.html**	YES/NO
1.6	**Will financial inducements (cash, vouchers or a prize draws) be offered to participants?**	YES/NO
1.7	**Will the study involve patients or patient data in the NHS?**	YES/NO

If you have answered 'NO' to all questions 1.1 to 1.7 above, please complete this form and submit TWO copies to Lainey Clayton in room F43. Both forms will be stamped as evidence of submission. One copy will be retained by the School for audit/office purposes and the other by the researcher/s. Undergraduate and postgraduate students should include/bind their copy of the form with their research report or dissertation.

If you have answered 'YES' to any of the questions above, you will need to complete a full ethical review form (ETHICS 2, available on Learning Central – CARBS RESEARCH ETHICS)

ETHICS 1

SURNAME: Scedrova

SECTION 2 PROJECT DETAILS

Title of Project:	**Modelling The Explanatory Bases Of Successful Open Innovation: A Longitudinal Analysis Using Project-Level Secondary Data**
Name of Lead Researcher:	**Ana Scedrova**
Status (please circle) :	**Undergraduate / MBA / MSc /Post Graduate Researcher /**
Names of other Researchers:	**N/A**
Department:	**Marketing and Strategy**
Email:	**ScedrovaA1@cardiff.ac.uk**
Contact Address:	**29 Cwrt Boston, Windsor Village, Cardiff, CF24 2SF**
Telephone number:	**07914279893**
Start and Estimated End Date of Project:	**01.10.2012-31.09.2016**

SECTION 3 STUDENTS ONLY

Module name and number	**PhD Business Studies**
Supervisor's or Module Leader's name	**Robert E. Morgan**
Email address	**morganre@cardiff.ac.uk**

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Research Ethics Committee
Cardiff Business School
Cardiff University

SECTION 4

Briefly describe the study design to be applied in the project including methods of data collection and data analysis

The proposed doctoral project is quantitatively focused with multiple levels of analysis, and involves secondary data gathering from publicly available sources. It uses information on firms, projects and individuals that participated in the Small Business Innovation Research (SBIR) programme. This initiative is administered through the U.S. Small Business Administration (SBA) and is funded by one of the eleven Federal Agencies. The primary datasets are retrieved from the SBIR and RePORTER public databases and then complemented with a number of other open sources, including Hoover's and ZoomInfo online databases. Data on patenting activity is gathered through PatBase. To examine human capital characteristics, relevant information is extracted from LinkedIn profiles of firm members as well as other public sources, including company websites and the Scopus database.
Quantitative measures are generated in line with existing literature or developed using econometric stochastic frontier estimation (SFE) method. In addition to descriptive statistics and correlation, data are analysed using OLS, Logit and Seemingly Unrelated regression techniques using STATA, R and SPSS statistical software.

~~**Please attach a copy of the questionnaire and all briefing documents which will be given to participants**~~ (NO Quest...)

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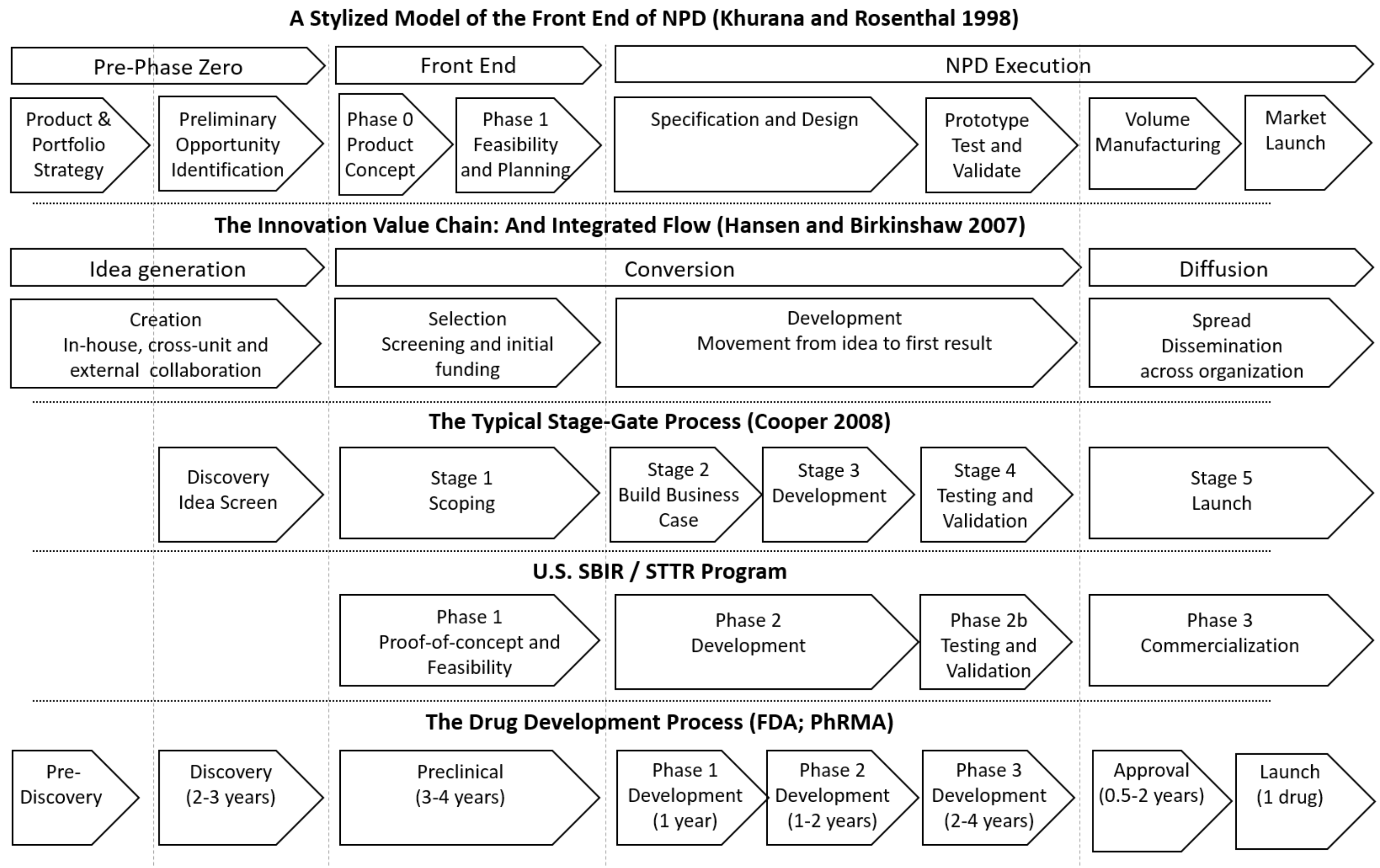
Research Ethics Committee
Cardiff Business School
Cardiff University

SECTION 5 DECLARATION

I/we hereby confirm that we have answered these questions to the best of our knowledge and will take all reasonable steps to ensure the independence and transparency of this research.
SIGNED: ~~~~~ **DATE: 10.09.2013** **PRINCIPAL RESEARCH INVESTIGATOR**
SIGNED: ~~~~~ **DATE: 10.09.2013** **SUPERVISOR (WHERE APPROPRIATE)**

ETHICS 1

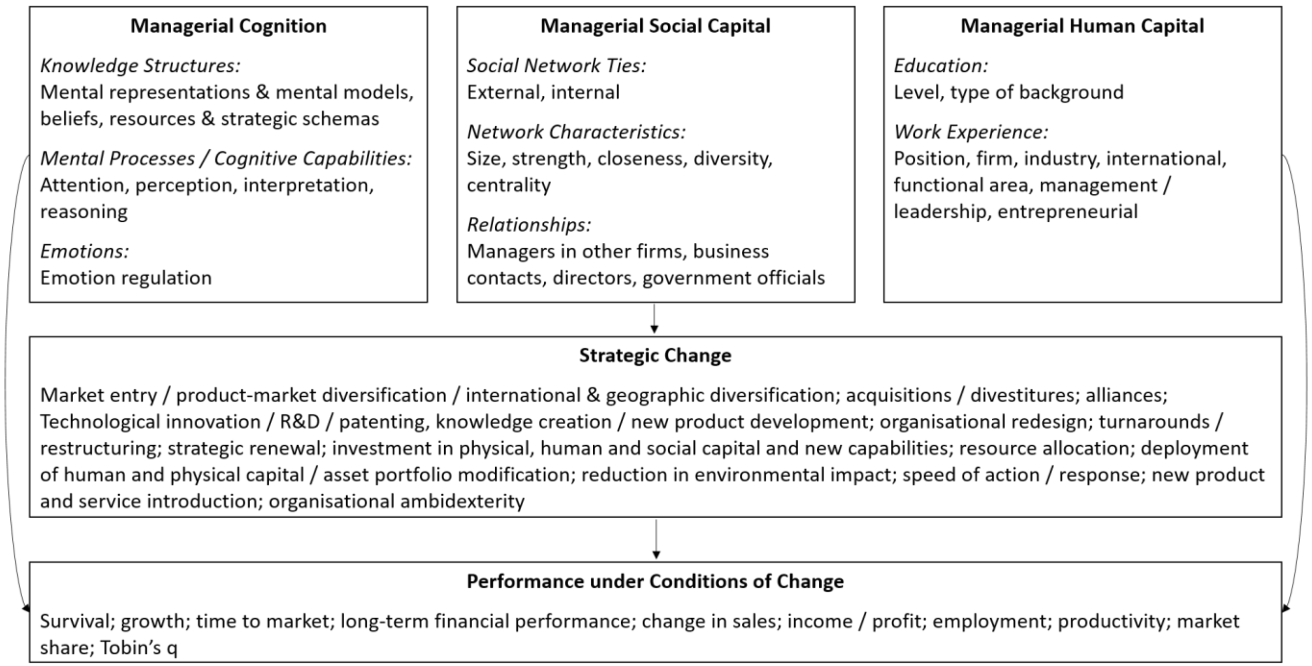
Appendix 3: Idea conversion models compared



Appendix 4: Summary of stochastic frontier estimation results

	Managerial Capability		PI's Intellectual Capability		R&D Capability	
	Variable	Coefficient estimate	Variable	Coefficient estimate	Variable	Coefficient estimate
Input 1	Commercial experience	0.0900*	Quality-adjusted academic competence	0.2004***	Quality-adjusted global patenting output	0.3149***
Input 2	Inventive capacity	0.0451	Knowledge appropriation	0.0377	Knowledge breadth	0.3183***
Input 3			Inventive capacity	0.0010	PI's intellectual capability	0.1234
Output (Intercept)	Innovation proliferation	3.4408***	Academic impact	3.4025***	Invention activity	0.4592

Appendix 5: Summary of variables measuring elements of the dynamic managerial capabilities construct



Source: Adapted from Helfat and Martin 2015, p. 1291

Appendix 6: Cases identified as candidates for deletion due to excessive levels of missing values

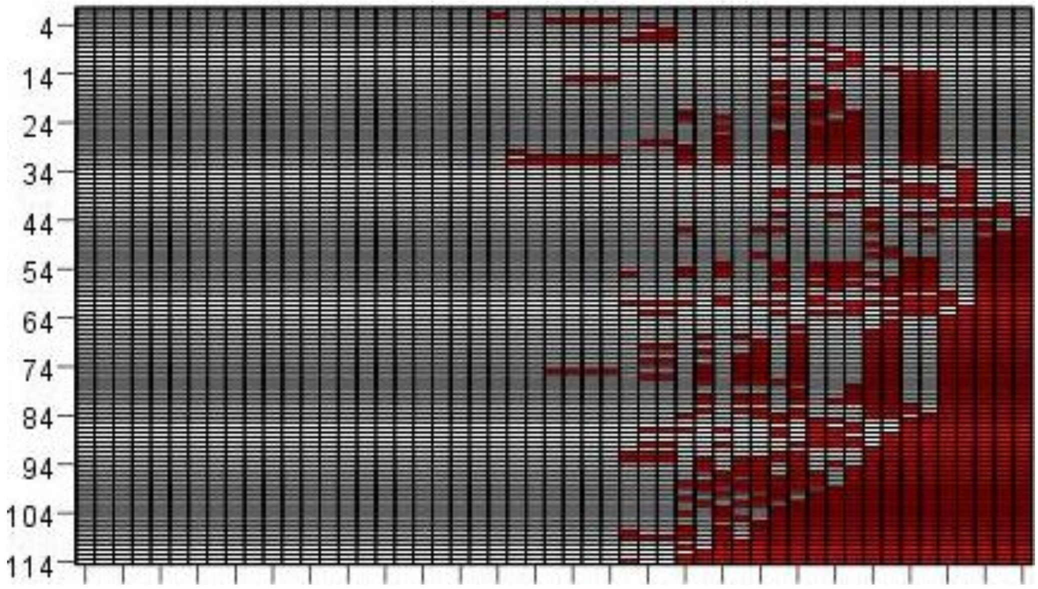
Case #	# Missing	% Missing
53	81	51.3
235	78	49.4
56	78	49.4
18	78	49.4
221	74	46.8
257	69	43.7
103	64	40.5

Appendix 7: Univariate analysis of variables to identify the extent of missing values

#[39]	Variable	# Missing	% Missing	Valid N	Mean	Std. Deviation
(1)	Manager's commercial experience	132	35.1%	244	13.35	9.37
(2)	Manager's technical experience	132	35.1%	244	14.91	12.85
(3)	Manager's entrepreneurial experience	131	34.8%	245	6.66	8.44
(4)	Manager's elite education	117	31.1%	259	27.38	28.71
	Manager's MBA	113	30.1%	263	-	-
(5)	PI's entrepreneurial experience	112	29.8%	264	4.44	6.45
(6)	PI's technical experience	112	29.8%	264	17.11	10.15
	Manager's professorship	110	29.3%	266	-	-
(7)	Manager's firm tenure	99	26.3%	277	6.74	6.21
(8)	PI's elite education	89	23.7%	287	25.86	26.33
	PI's professorship	88	23.4%	288	-	-
	PI's MBA	83	22.1%	293	-	-
	Manager's PhD	81	21.5%	295	-	-
(9)	PI's firm tenure	80	21.3%	296	5.37	5.30
	Manager CEO	76	20.2%	300	-	-
(10)	Manager's publications	57	15.2%	319	30.03	69.29
	PI's PhD	55	14.6%	321	-	-
(11)	Manager's patents	49	13.0%	327	4.57	12.27
	PI's CEO	39	10.4%	337	-	-
(12)	Sales performance	22	5.9%	354	6.65	75.60
(13)	Employment performance	21	5.6%	355	30.09	162.97
(14)	Firm age	10	2.7%	366	8.93	7.87
(15)	PI's knowledge appropriation	8	2.1%	368	0.84	1.28
(16)	PI's citations	8	2.1%	368	720.45	1554.07
(17)	PI's h-index	8	2.1%	368	14.71	11.14
(18)	PI's publications	6	1.6%	370	30.71	41.17
(19)	PI's patents	4	1.1%	372	5.85	14.56
(20)	Project duration (post-funding)	2	0.5%	374	433.04	218.64
	Project category	1	0.3%	375	-	-
(21)	Industry volatility (t)	0	0.0%	376	28.76	23.16
	Industry volatility (2014)	0	0.0%	376	18.32	6.25
(22)	Innovation performance	0	0.0%	376	7.93	24.18
(23)	Global patenting output	0	0.0%	376	5.39	17.43
(24)	Knowledge breadth	0	0.0%	376	3.21	5.33
(25)	Innovation proliferation	0	0.0%	376	4.93	6.95
(26)	Invention activity (post-funding)	0	0.0%	376	3.95	11.04
(27)	Initial commitment (project)	0	0.0%	376	.18	.15
(28)	State innovativeness	0	0.0%	376	67.71	15.36
(29)	Phase I prior investment ($)	0	0.0%	376	0.93	1.76
(30)	Phase I prior investment (# of awards)	0	0.0%	376	7.36	15.85
(31)	Phase II prior investment ($)	0	0.0%	376	1.83	4.25
(32)	Phase II prior investment (# of awards)	0	0.0%	376	2.43	6.27
(33)	Total prior investment ($)	0	0.0%	376	2.76	5.81
(34)	Total prior investment (# of awards)	0	0.0%	376	9.80	21.73
(35)	Abstract readability	0	0.0%	376	20.40	3.16
	Discontinuation	0	0.0%	376	-	-
	Year cohort	0	0.0%	376	-	-
	Project scope	0	0.0%	376	-	-
	Non-woman-owned	0	0.0%	376	-	-
	Non-minority-owned	0	0.0%	376	-	-
	Non-HubZone-owned	0	0.0%	376	-	-

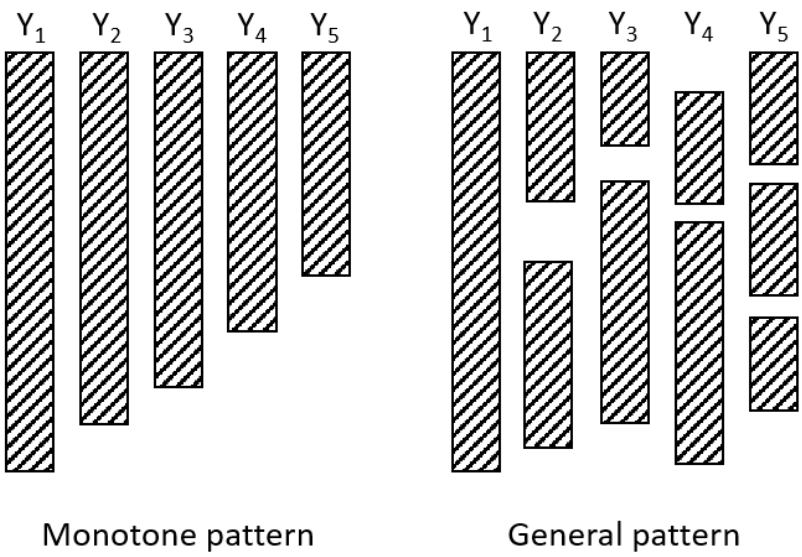
[39] Variable numbers are used in Appendix 10.

Appendix 8: Missing value patterns



Note: Red cells depict missing cases

Appendix 9: Examples of missing data patterns: monotone pattern on the left, general pattern on the right



Source: Adopted from Little and Rubin (2002, p.5)

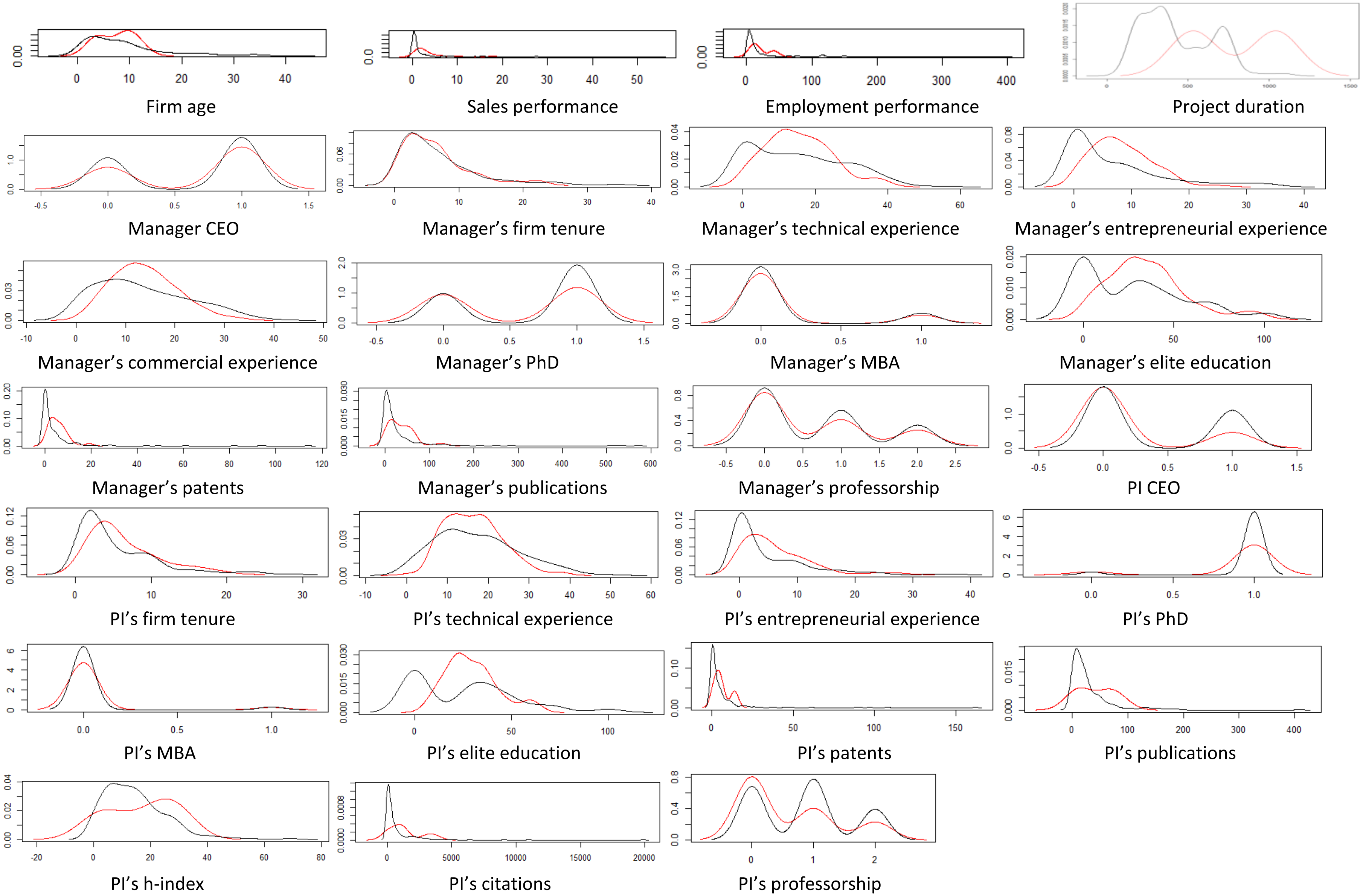
Appendix 10: Results of t-tests between the means of missing and non-missing data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Firm age	-	-	-	1.3	-	-	-	16.7***	-	3.6***	-0.1	1.6	3.2***	-	2.0*	1.9*	2.8**	4.7***
Sales performance	-0.2	-1.0	-1.2	-0.1	-0.8	0.1	-0.1	0.2	-0.5	3.8***	1.1	-	-0.7	0.9	2.4**	2.8**	2.8**	0.9
Employment performance	-0.4	-1.2	-1.0	0.4	-0.4	-0.1	-0.6	0.3	-1.0	3.7***	0.9	-	-	0.5	2.2**	2.4**	2.2**	0.6
Manager's firm tenure	-3.6	-0.1	-	-0.1	3.2***	1.0	-	-0.6	2.1**	0.7	4.0***	0.8	0.5	-1.3	1.9*	0.3	1.0	-0.1
Manager's technical exper.	-5.7**	-	-0.4	-1.6	3.1***	2.2**	-0.6	0.1	1.9*	1.0	3.7***	0.9	1.0	-0.6	2.2**	0.5	1.7	0.4
Manager's entrepren. exper.	-3.6	-0.1	-	-1.9*	3.8***	1.9*	-0.5	-0.4	2.4**	0.6	3.1***	0.9	1.0	-0.6	1.7*	0.4	1.4	0.3
Manager's commercial exper.	-	0.4	6.9***	-2.2**	3.9***	2**	0.0	-0.3	2.5**	0.6	3.1***	1.0	1.1	-0.4	1.7*	0.3	1.2	0.2
Manager's elite education	-1.8	-0.4	0.1	-	2.7***	1.1	0.9	-0.7	1.5	0.3	4.4***	0.9	0.8	-0.8	1.5	-0.1	0.3	-0.4
Manager's patents	-	-	-	-	4.3***	0.2	-	-1.1	3.9***	-	-	1.0	1.0	0.7	2.1**	-0.2	0.4	-0.5
Manager's publications	-	-	-	-	4.2***	0.9	-	-1.4	3.2***	-	6.8***	1.1	1.1	0.6	2.5**	0.0	0.7	-0.2
PI's firm tenure	-1.7*	-0.1	-1.1	-1.9*	1.6	0.0	-2.7**	0.1	-	-1.9*	-1.6	1.1	1.0	-2.0**	1.3	0.6	1.8**	0.8
PI's technical experience	-2.3**	0.4	0.0	-1.5	-0.6	-	-1.7*	-0.8	-1.0	-1.4	-1.3	1.0	0.9	-1.1	1.4	1.5	2.3**	2.2**
PI's entrepreneurial exper.	-2.3**	0.2	0.0	-1.7	-	0.7	-1.7*	-0.2	-1.0	-1.8*	-1.4	1.0	0.9	-1.4	1.3	1.5	2.3**	2.1**
PI's elite education	-1.7*	-0.3	-0.8	-2.0*	0.9	0.2	-2.2*	-	0.3	-1.9*	-1.5	0.6	0.3	-2.4**	1.1	1.3	0.9	0.8
PI's patents	-0.2	0.5	1.6	0.9	-	-	2.5*	-	-	0.7	2.6**	0.5	-0.2	4.7**	-	-	-	-
PI's publications	-0.2	-0.5	0.5	1.4	-1.1	-1.8	0.5	16.7***	-0.9	-0.7	-0.6	0.8	0.3	1.8	-	-	-	-
PI's h-index	0.0	-1.1	1.3	2.5**	-1.1	-1.8	0.9	-0.5	-2.6*	-0.4	-0.8	1.0	0.6	-0.3	-	-	-	-11.8***
PI's citations	0.0	-1.1	1.3	2.5**	-1.1	-1.8	0.9	-0.5	-2.6*	-0.4	-0.8	1.0	0.6	-0.3	-	-	-	-11.8***
PI's knowledge appropriation	0.0	-1.1	1.3	2.5**	-1.1	-1.8	0.9	-0.5	-2.6	-0.4	-0.8	1.0	0.6	-0.3	-	-	-	-11.8***
Manager CEO	-	-	-	-0.9	2.8**	0.9	-	-1.1	2.3**	-0.7	2.6**	1.2	1.5	0.2	1.6	-0.3	0.5	-0.6
Manager's PhD	-	-	-	-	3.2***	1.0	-7.7**	-1.1	2.1**	-0.3	4.9***	1.1	1.2	-0.2	1.9*	-0.2	0.7	-0.4
PI's MBA	-1.7	0.4	1.3	0.4	3.9***	1.7	0.6	-0.4	2.3**	0.3	4.7***	0.8	0.7	-0.8	1.7*	0.3	0.7	-0.3
PI's CEO	0.0	0.4	0.6	-1.8*	-	0.7	-1.1	16.7***	-	-0.4	1.6	1.3	2.0**	-0.8	0.7	2.5	2.4**	1.3
PI's PhD	-0.5	1.5	1.7	-2.1**	-	-	-1.7*	-	-3.1**	2.2***	2.8***	0.9	1.3	-2.0*	3.6***	3.4	4.3***	3.1***
PI's MBA	-2.5**	1.0	-0.7	-2.0**	0.8	0.6	-1.9*	-0.2	-0.1	-1.8**	-1.4	1.0	1.0	-1.4	2.0**	1.9	2.6**	2.0**

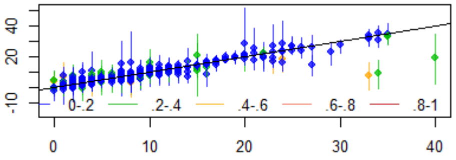
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)
Firm age	0.8	-2.0*	3.6***	6.4***	6***	11.7***	13.9***	6.9***	1.7	0.6	9.8***	8.5***	7.8***	6.9***	8.7***	8.3***	-0.5
Sales performance	0.4	0.3	5.3***	4.5***	4.3***	4.8***	3.1**	4.5***	0.5	1.6	3.3***	2.0*	2.1**	1.6	2.5**	1.9*	-0.1
Employment performance	-0.3	0.4	5.1***	4.7***	4.2***	6.1***	3.1**	5.2***	2.7**	1.6	3.0**	1.8*	2*	1.5	2.3**	1.7	-0.3
Manager's firm tenure	2.0**	-1.2	1.1	0.6	0.4	-0.9	1.1	1.3	1.1	-0.4	0.3	-0.4	2*	0.3	1.5	-0.2	0.6
Manager's technical exper.	2.7**	-1.1	0.8	1.7	1.5	0.1	2.8**	2**	1.2	0.6	0.0	-0.5	1.7*	0.3	1.2	-0.3	-0.8
Manager's entrepren. exper.	2.6**	-0.7	0.7	1.6	1.4	-0.1	2.4**	1.9*	1.1	0.1	-0.1	-0.6	1.7	0.2	1.1	-0.4	-0.7
Manager's commercial exper.	2.7**	-1.0	0.6	1.7*	1.5	0.2	2.8**	2.1**	1.2	0.6	0.3	-0.4	1.8*	0.3	1.4	-0.2	-0.5
Manager's elite education	2.2**	-0.3	0.9	1.2	1.0	-0.3	1.6	1.6	1.3	1.0	0.7	-0.1	1.6	0.2	1.4	0.0	-1.0
Manager's patents	2.8**	0.0	-0.8	0.8	0.7	1.1	2.4**	1.3	0.4	-2.6**	2.0**	1.4	2.1**	1.3	2.2**	1.4	0.7
Manager's publications	2.9***	0.2	0.1	1.1	1.0	1.5	2.7**	1.6	0.9	-1.3	2.7**	1.9*	3.7***	1.9*	3.5***	1.9*	0.7
PI's firm tenure	2.9***	-1.0	1.7*	-1.9*	-1.9*	-0.2	-0.1	-1.1	0.0	1.8*	-0.6	-1.0	0.5	0.5	0.1	-0.7	1.1
PI's technical experience	-0.4	-1.2	1.3	-1.7*	-1.8*	0.4	0.6	-0.8	-0.2	2.6**	-0.6	-1.1	-0.1	0.3	-0.3	-0.8	0.2
PI's entrepreneurial exper.	-0.4	-1.1	1.3	-1.7*	-1.8*	0.5	0.7	-0.8	-0.4	2.2**	-0.6	-1.1	-0.1	0.3	-0.3	-0.8	0.1
PI's elite education	2.4**	-0.8	1.7*	-2.5**	-2.7**	-1.7*	-0.4	-1.7*	-0.2	1.9*	-1.3	-2.1**	0.4	-0.8	-0.2	-1.8*	-0.5
PI's patents	-	1.4	1.7	2.9**	5.5***	2.2	1.2	0.3	-0.9	1.4	2.7**	4.4***	5.7***	5.4***	5.4***	4.8***	-0.9
PI's publications	5.9***	2.6**	1.5	3.9***	5.5***	3.0**	1.8	1.0	-0.8	0.3	4.0***	5.4***	6.8***	6.3***	6.5***	5.8***	-0.5
PI's h-index	-1.6	0.3	1.6	3.8***	3.8***	2.6**	1.1	1.6	-0.7	0.8	3.6***	2.4**	3.8***	2.7***	4.0***	2.5**	-0.2
PI's citations	-1.6	0.3	1.6	3.8***	3.8***	2.6**	1.1	1.6	-0.7	0.8	3.6***	2.4**	3.8***	2.7***	4.0***	2.5**	-0.2
PI's knowledge appropriation	-1.6	0.3	1.6	3.8***	3.8***	2.6**	1.1	1.6	-0.7	0.8	3.6***	2.4**	3.8***	2.7***	4.0***	2.5**	-0.2
Manager CEO	2.0**	-0.6	0.3	2.3**	2.1**	2.7**	3.6***	3.1***	1.3	0.5	1.5	0.8	2.6**	1.7*	2.3**	1.0	1.1
Manager's PhD	2.0**	-0.6	1.3	1.5	1.3	1.5	2.5**	2.2**	1.4	0.0	1.2	0.4	1.9*	0.8	1.7*	0.5	0.0
PI's MBA	2.2**	-1.5	1.7	1.0	0.8	-0.6	1.6	1.4	1.3	0.7	0.3	-0.5	1.3	-0.1	1.0	-0.4	-0.5
PI's CEO	5.2***	-1.2	0.5	3.8***	3.6***	2.4**	4.9***	4.3***	-0.6	2.7**	1.7	1.7	2.3**	2.2**	2.1*	1.8*	1.0
PI's PhD	4.4***	-1.2	2.0**	-0.3	-0.5	-0.8	1.4	2.0**	-0.5	1.9*	-0.9	-1.3	-0.5	-0.5	-0.7	-1.2	1.0
PI's MBA	2.8**	-1.0	2.5**	-2.0**	-2.1**	-0.4	0.4	-1.2	0.1	2.6**	-0.6	-1.3	0.4	0.2	0.0	-1.0	1.3

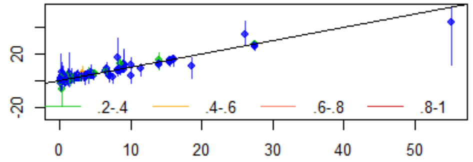
Notes: Significance levels (* <0.1, ** <0.05, ***<0.01); For each quantitative variable, pairs of groups are formed by indicator variables. Indicator variables with less than 1% missing are not displayed.

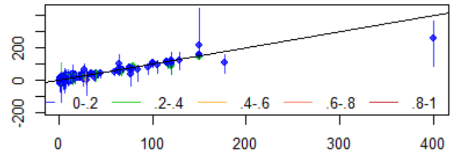
Appendix 11: Diagnostics of imputed variables – density plots

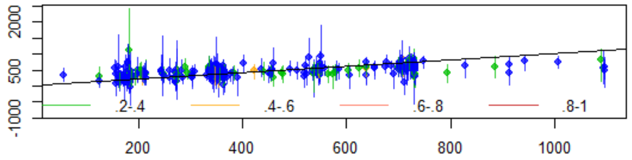


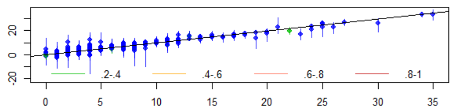
Appendix 12: Diagnostics of imputed variables – overimputation[40]

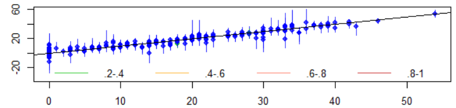

Firm age

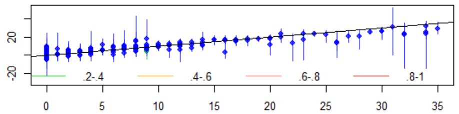

Sales performance

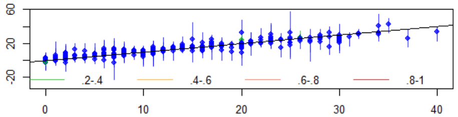

Employment performance

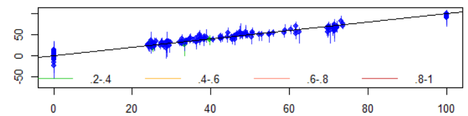

Project duration

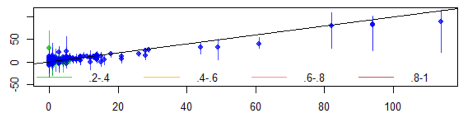

Manager’s firm tenure

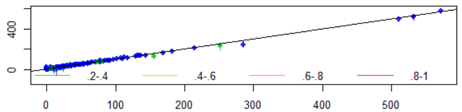

Manager’s technical experience

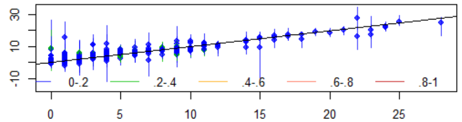

Manager’s entrepreneurial experience

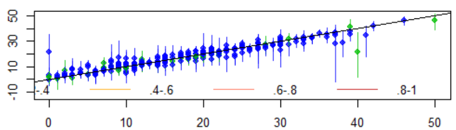

Manager’s commercial experience

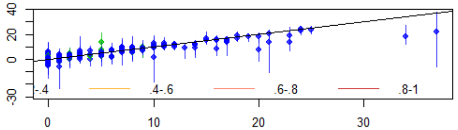

Manager’s elite education

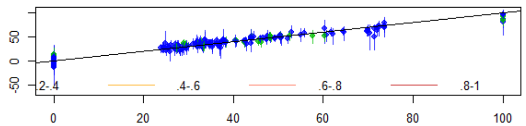

Manager’s patents

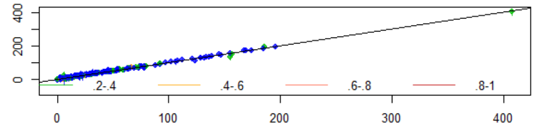

Manager’s publications

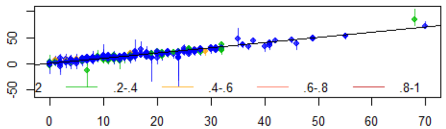

PI’s firm tenure

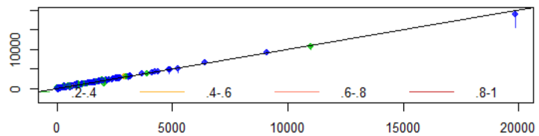

PI’s technical experience

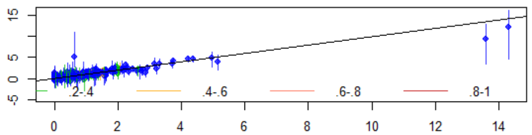

PI’s entrepreneurial experience


PI’s elite education


PI’s publications


PI’s h-index


PI’s citations


PI’s knowledge appropriation

[40] Vertical axes depict imputed values, horizontal axes depict observed values

Appendix 13: Sensitivity analysis of original versus imputed data – means and standard deviations compared[41]

Statistic	Firm age	Sales performance	Employment performance	Project duration	Manager CEO	Manager's firm tenure	Manager's technical experience	Manager's entrepreneurial experience	Manager's commercial experience	Manager's PhD	Manager's MBA	Manager's elite education	Manager's patents	Manager's publications
Sample 0 mean	8.93	2.64	21.70	432.98	0.62	6.74	14.93	6.65	13.36	0.66	0.15	27.29	4.57	30.12
Samples 1-5 average mean	8.89	2.71	21.65	434.86	0.62	6.64	15.12	7.20	13.53	0.64	0.17	29.74	4.72	30.92
Discrepancy in means	-0.04	0.07	-0.05	**1.88**	0.00	-0.10	0.18	0.54	0.17	-0.03	0.02	**2.45**	0.15	0.80
Sample 0 standard deviation	7.88	5.67	39.72	218.93	0.49	6.22	12.87	8.46	9.38	0.47	0.36	28.73	12.29	69.38
Samples 1-5 average standard deviation	7.83	5.69	39.12	220.72	0.49	6.11	12.36	7.91	9.26	0.48	0.38	28.62	11.66	65.43
Discrepancy in standard deviations	-0.04	0.02	-0.60	**1.79**	0.00	-0.11	-0.51	-0.55	-0.13	0.01	0.02	-0.11	-0.62	**-3.95**

Statistic	Managers professor	PI CEO	PI's firm tenure	PI's technical experience	PI's entrepreneurial experience	PI's PhD	PI's MBA	PI's elite education	PI's patents	PI's publications	PI's h-index	PI's citations	PI's knowledge appropriation	PI professor
Sample 0 mean	0.67	0.38	5.39	17.12	4.45	0.96	0.04	25.86	5.75	30.73	14.66	721.78	0.84	0.84
Samples 1-5 average mean	0.70	0.38	5.59	16.91	4.90	0.94	0.06	26.74	5.76	30.91	14.71	735.63	0.86	0.83
Discrepancy in means	0.03	0.00	0.21	-0.21	0.45	-0.02	0.02	0.88	0.01	0.18	0.05	**13.85**	0.02	-0.02
Sample 0 standard deviation	0.76	0.49	5.31	10.16	6.46	0.20	0.21	26.37	14.44	41.23	11.20	1555.98	1.28	0.75
Samples 1-5 average standard deviation	0.78	0.49	5.41	9.92	6.52	0.24	0.24	25.89	14.38	41.22	11.23	1556.02	1.31	0.76
Discrepancy in standard deviations	0.01	0.00	0.11	-0.24	0.05	0.04	0.03	-0.48	-0.06	-0.01	0.03	0.04	0.03	0.01

[41] Sample 0 refers to the original dataset, samples 1-5 refer to five imputed datasets.

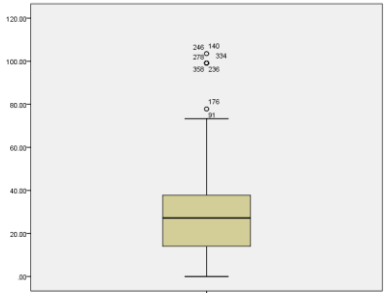
Appendix 14: Potential candidates for deletion based on z-scores

Case #	Frequency
153	18
151	17
152	17
150	15
294	8
268	7
337	7
282	6
295	6
115	4
225	4
188	3

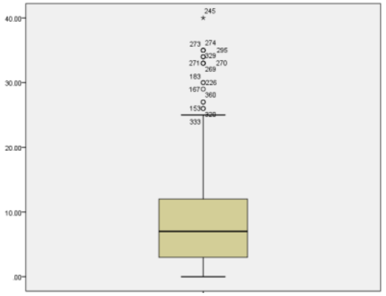
Appendix 15: Potential candidates for deletion based on Mahalanobis D^2

Case #	Frequency
225	5
337	5
268	4
153	3
87	1
110	1
113	1
374	1
84	1

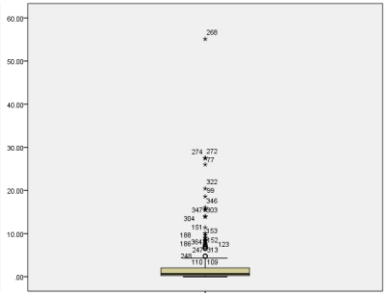
Appendix 16: Visual examination of outliers – box plots



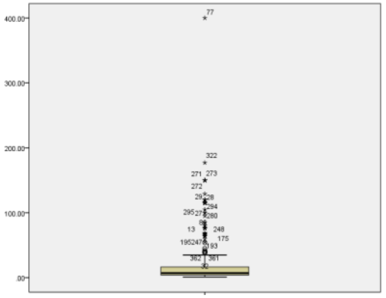
Industry volatility (t)



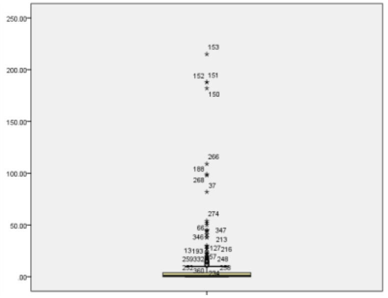
Firm age



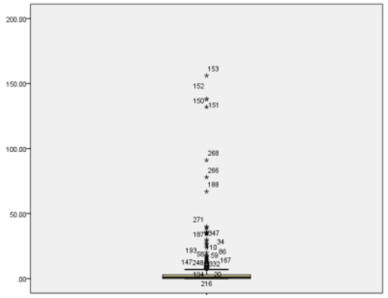
Sales performance



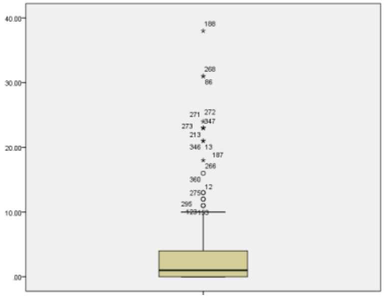
Employment performance



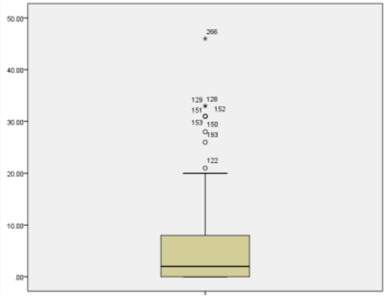
Innovation performance



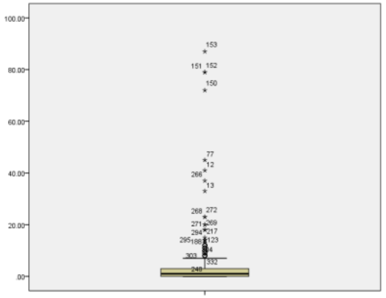
Global patenting output



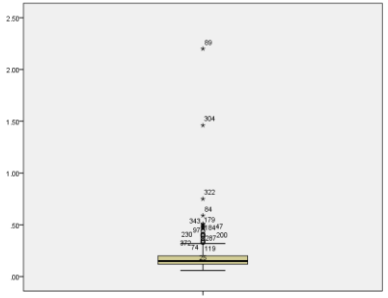
Knowledge breadth



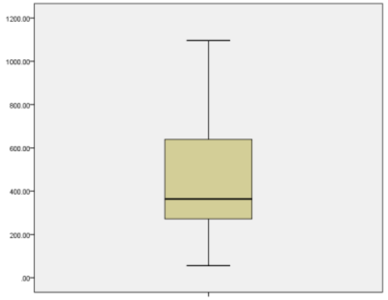
Innovation proliferation



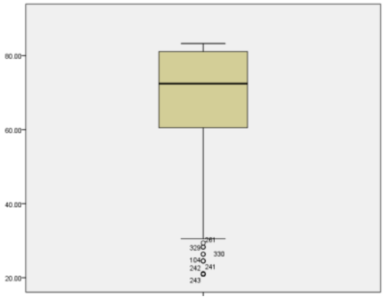
Post-funding invention activity



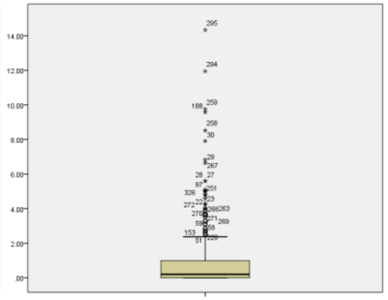
Initial commitment (project)



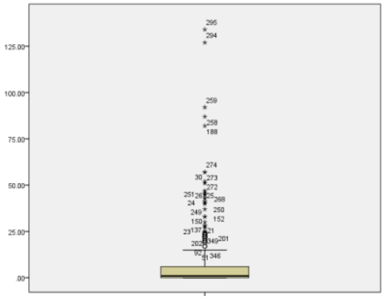
Project duration



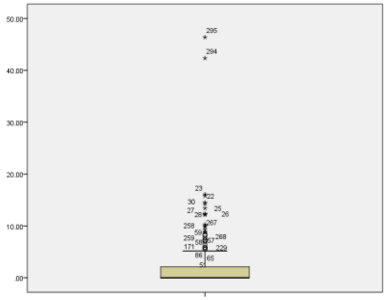
State innovativeness



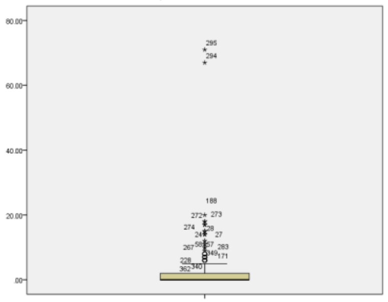
Phase I prior investment ($)

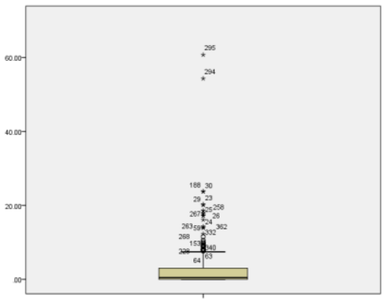


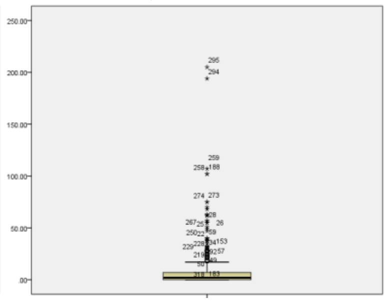
Phase I prior investment (# of awards)

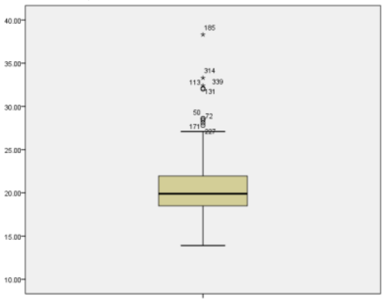


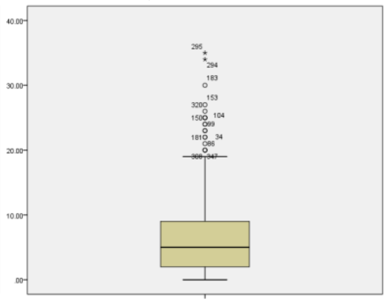
Phase II prior investment ($)



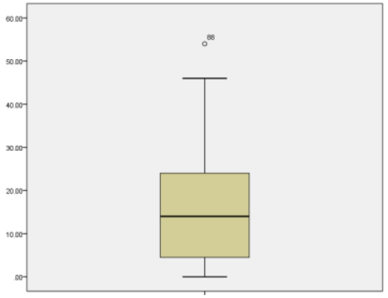
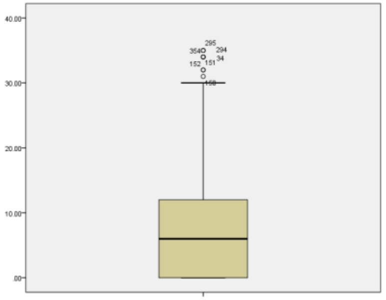
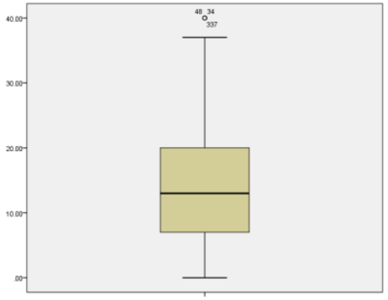
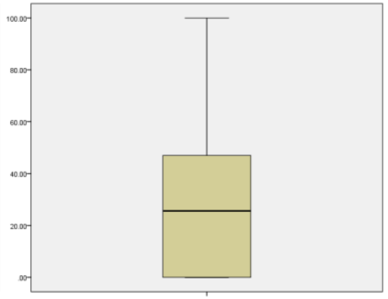
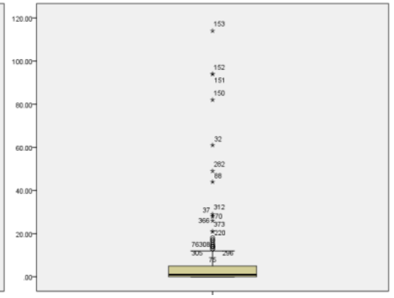




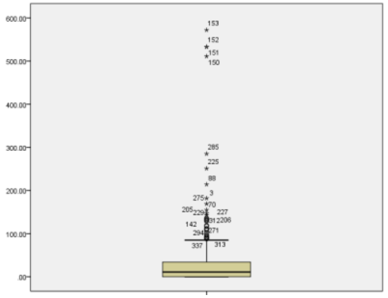
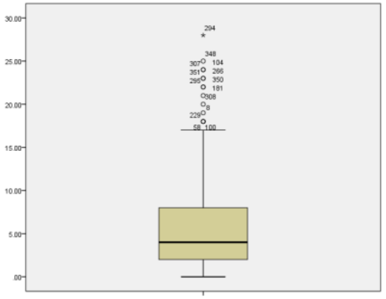
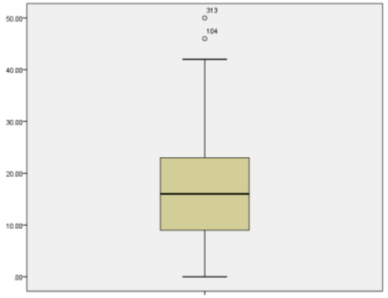
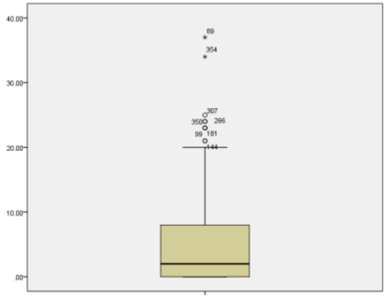
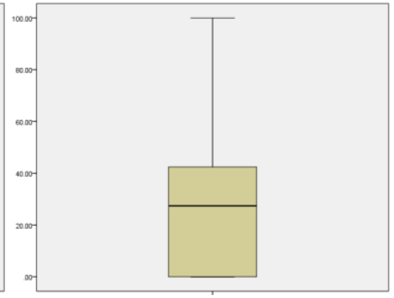




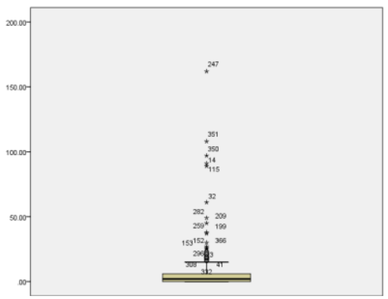
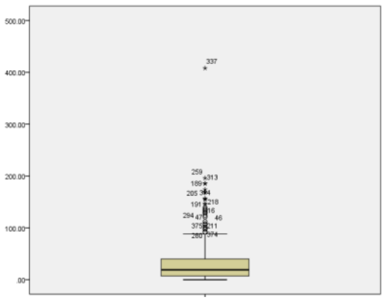
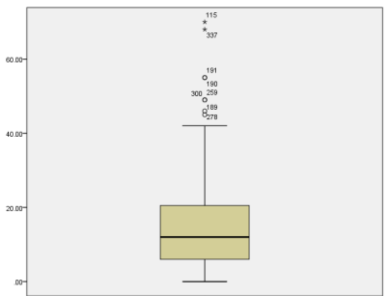
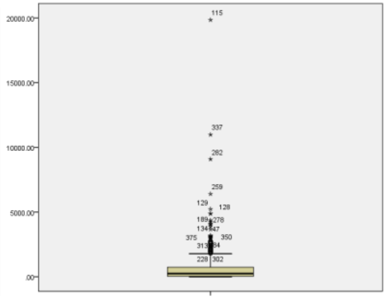
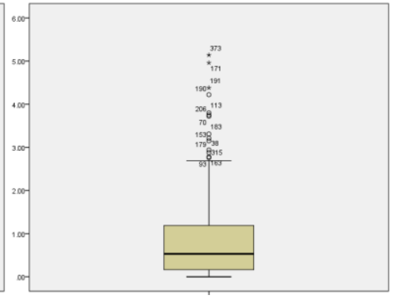
Phase II prior investment (# of awards) | Total prior investment ($) | Total prior investment (# of awards) | Abstract readability | Manager's firm tenure

Manager's technical experience | Manager's entrepreneurial experience | Manager's commercial experience | Manager's elite education | Manager's patents

Manager's publications | PI's firm tenure | PI's technical experience | PI's entrepreneurial experience | PI's elite education

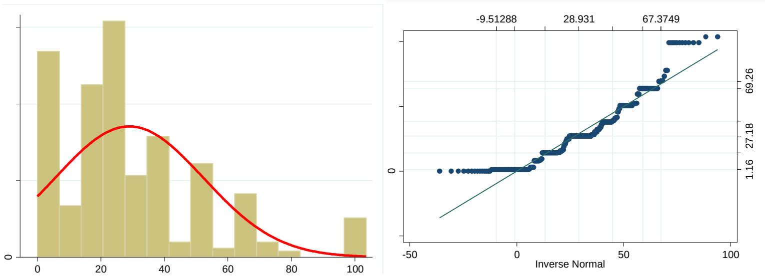






PI's patents | PI's publications | PI's h-index | PI's citations | PI's knowledge appropriation

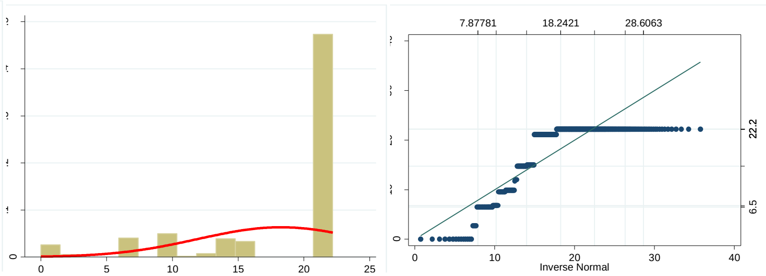
Appendix 17: Potential candidates for deletion based on box plots

Case #	Variable
245	Firm age
268	Sales performance
77	Employment performance
150,151, 152,153	Innovation performance, Post-funding invention activity, Global patenting output, Manager's patent's, Manager's publications,
188	Knowledge breadth
266	Innovation proliferation
304, 89	Initial commitment (project),
294, 295	All measures of Prior investment, Manager's firm tenure, Manager's entrepreneurial experience
185	Abstract readability, PI's firm tenure
88	Manager's technical experience
48, 34, 337	Manager's commercial experience
313, 104	PI's technical experience
89, 354	PI's entrepreneurial experience
247	PI's patents
337	PI's publications
115, 337	PI's h-index, PI's citations
373, 171	PI's knowledge appropriation

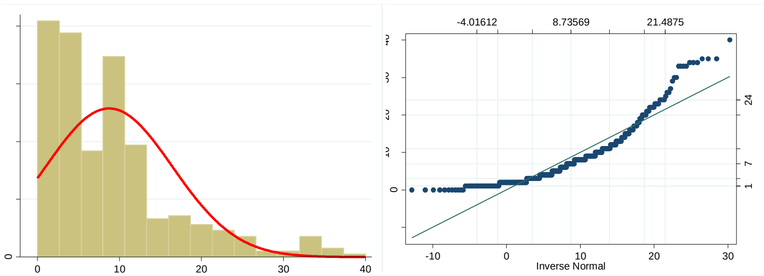
Appendix 18: Visual examination of data for normality assumption – histograms and normal probability Q-Q plots[42]



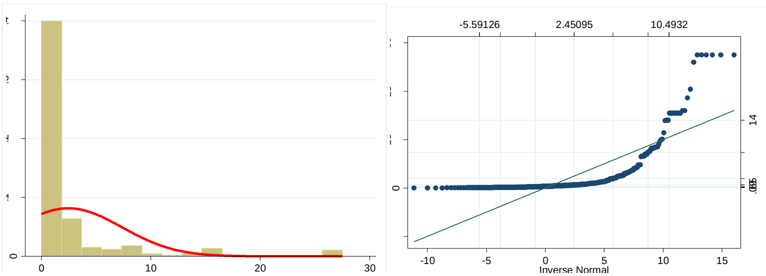
Industry volatility (t)



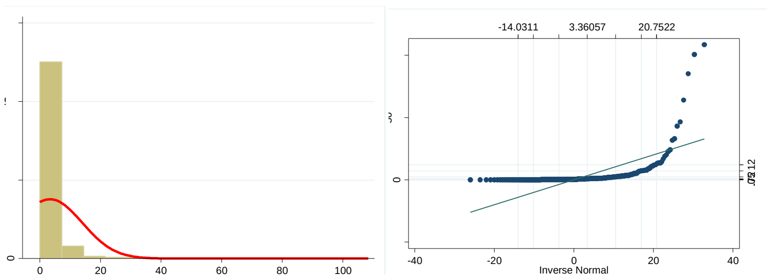
Industry volatility (2014)



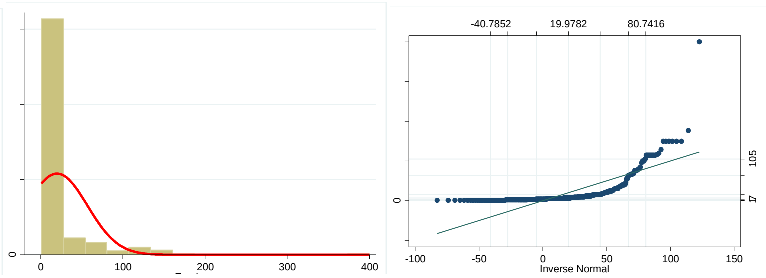
Firm age



Sales performance

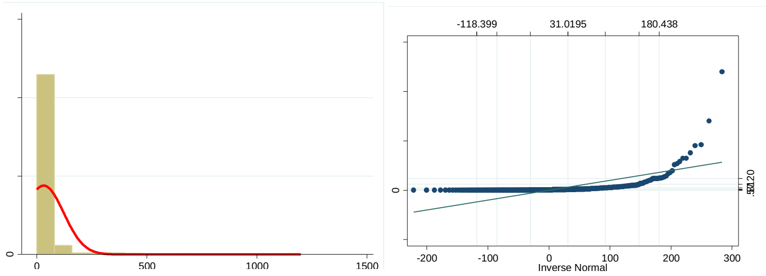


Sales yield

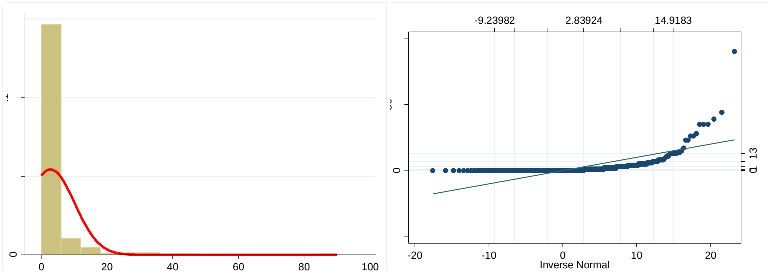


Employment performance

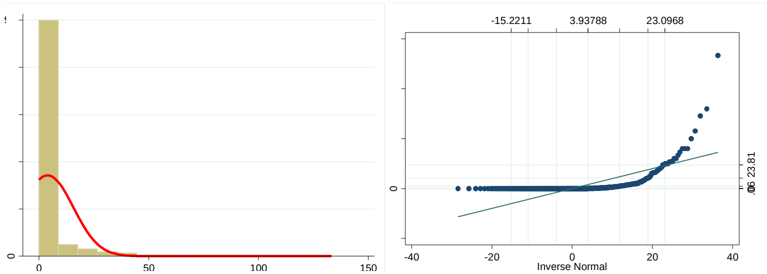
42 In Q-Q plots, gridlines are 5, 10, 25, 50, 75, 90 and 95 percentiles



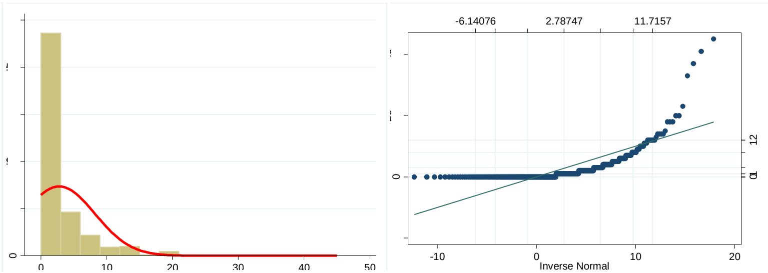
Employment yield



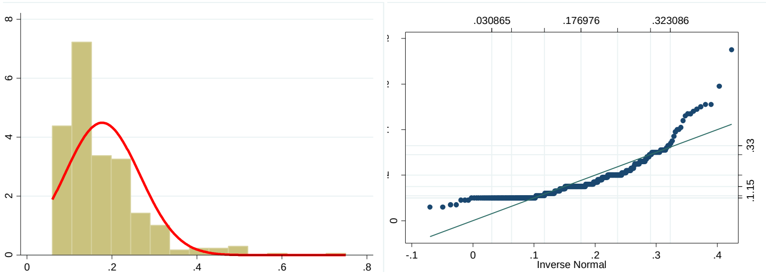
Innovation performance



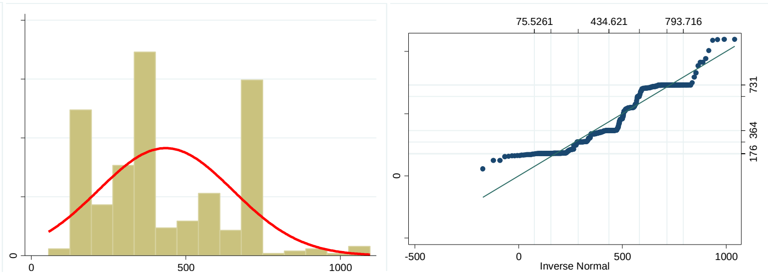
Innovation yield



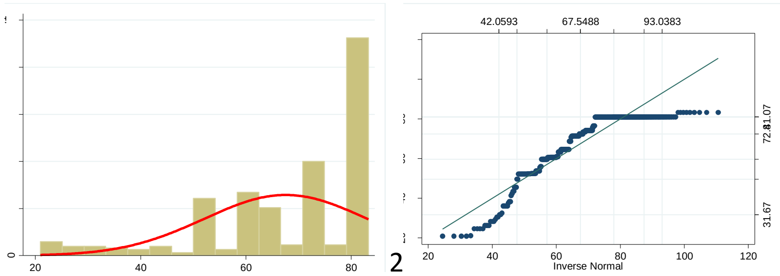
Post-funding invention activity



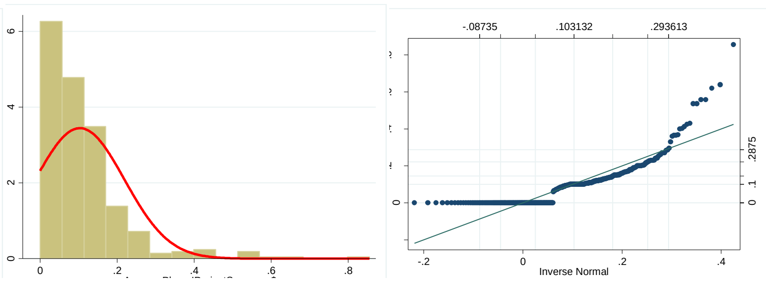
Initial commitment (project)



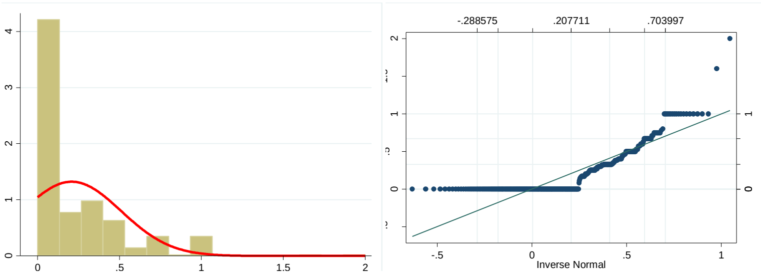
Project duration



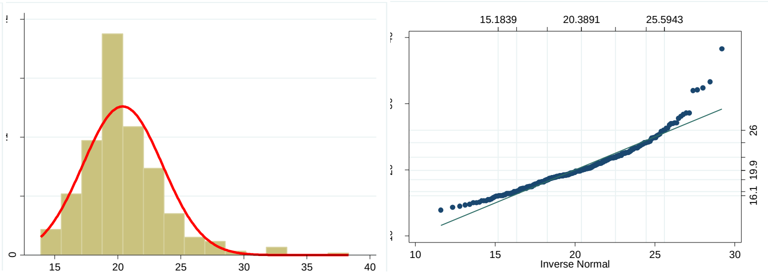
State innovativeness



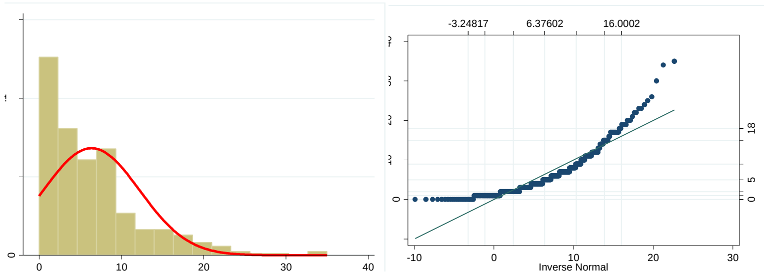
Initial commitment (portfolio)



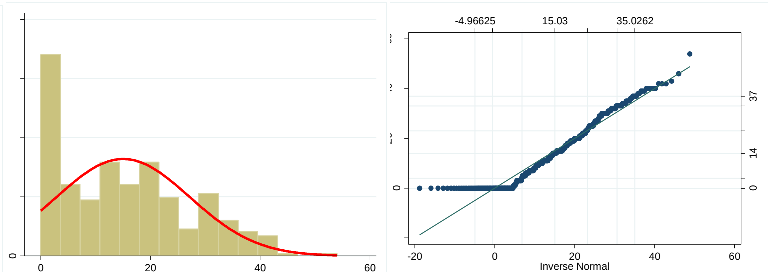
Sequencing



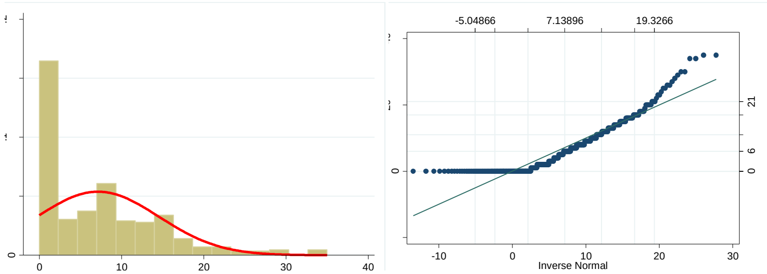
Abstract readability



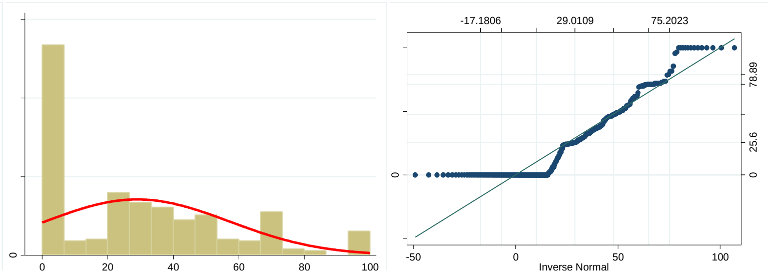
Manager's firm tenure



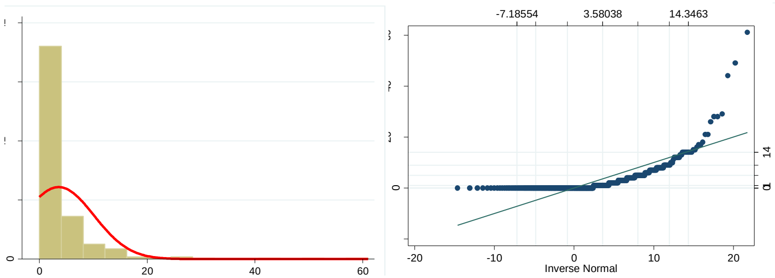
Manager's technical experience



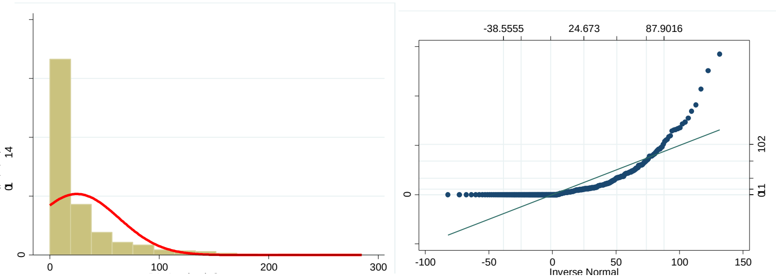
Manager’s entrepreneurial experience



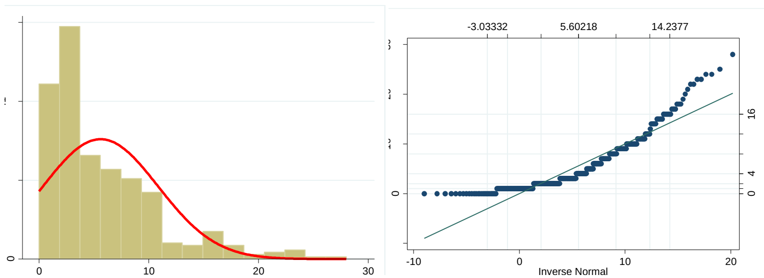
Manager’s elite education



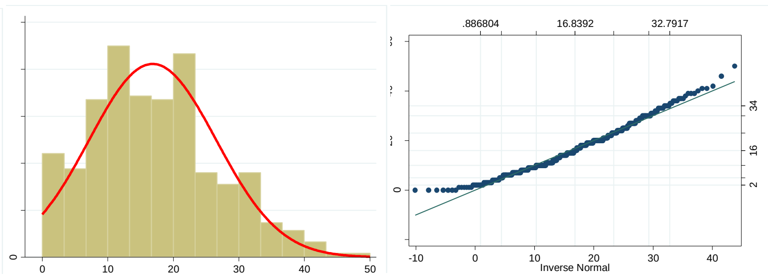
Manager’s patents



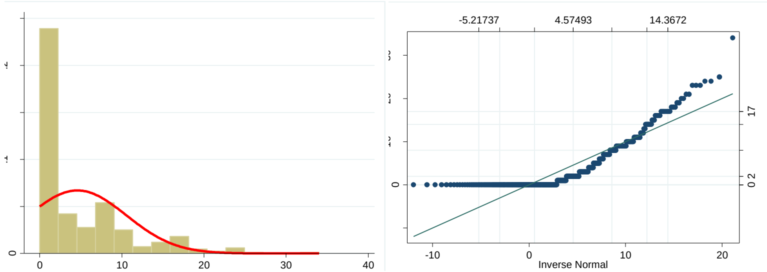
Manager’s publications



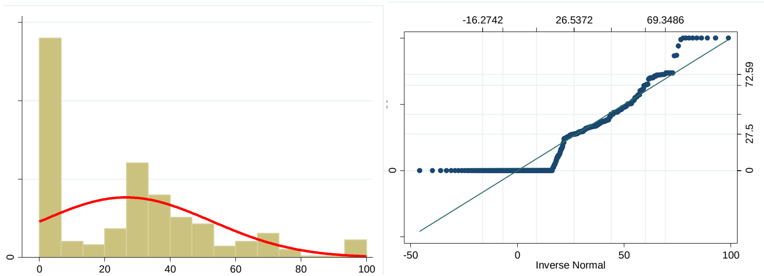
PI’s firm tenure



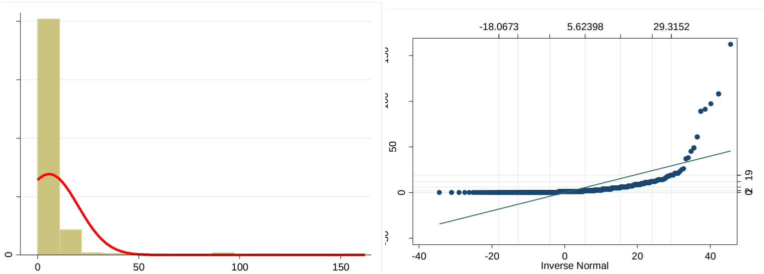
PI’s technical experience



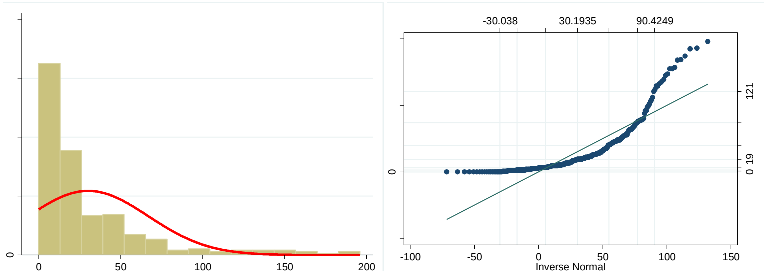
PI's entrepreneurial experience



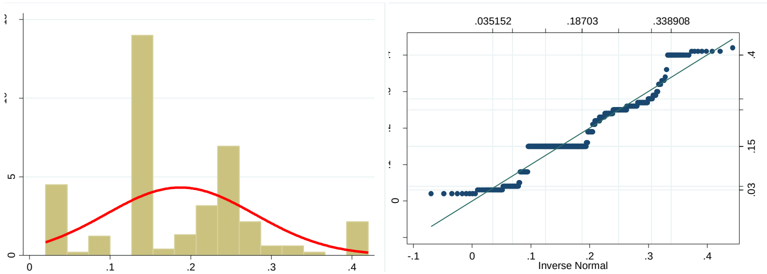
PI's elite education



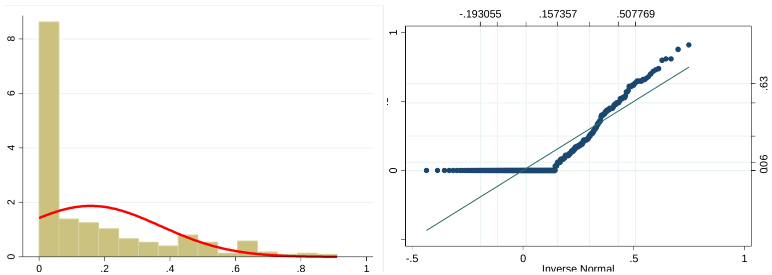
Manager's patents



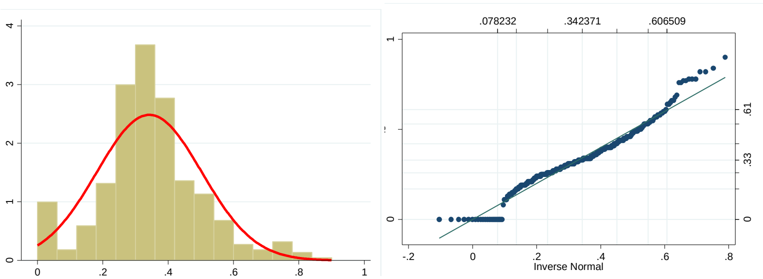
Manager's publications



R&D capability



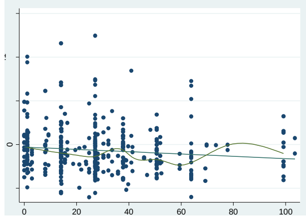
Managerial capability

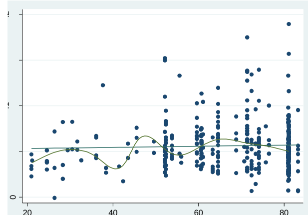


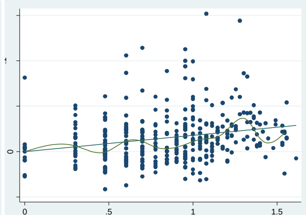
PI's intellectual capability

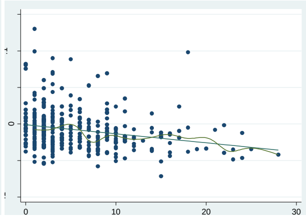
Appendix 19: Visual examination of data for linearity assumption – augmented component-plus-residual plots[43]

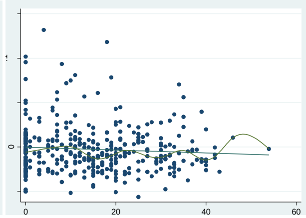
DV: Initial Commitment (project)

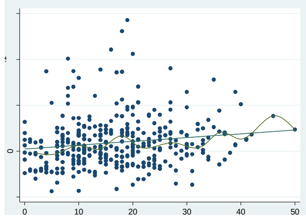

Industry volatility (t)

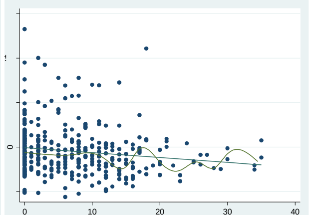

State innovativeness

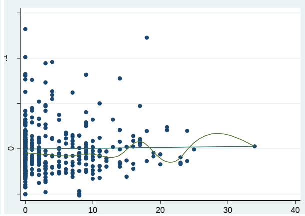

Firm age

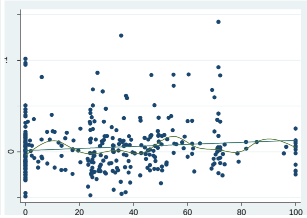

PI's firm tenure

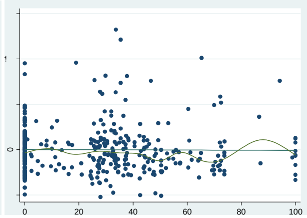

Manager's technical exper.

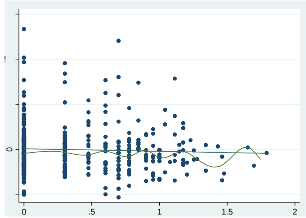

PI's technical experience

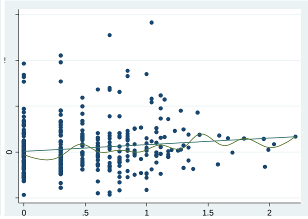

Manager's entrep. exper.

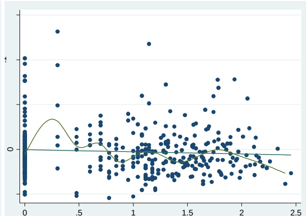

PI's entrep. experience

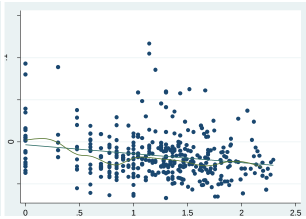

Manager's elite education

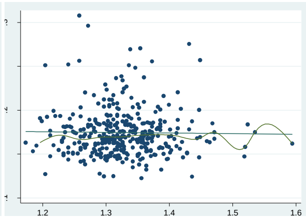

PI's elite education

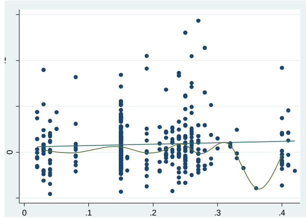

Manager's patents

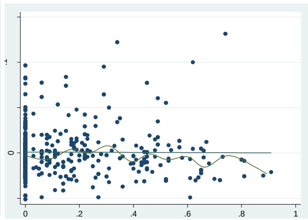

PI's patents

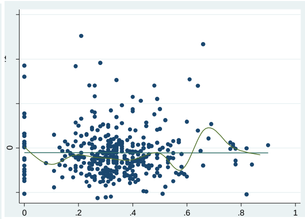

Manager's publications

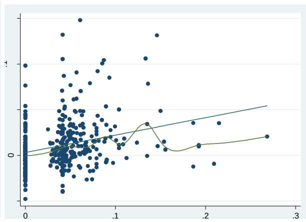

PI's publications

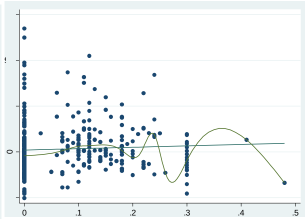

Abstract readability


R&D capability


Managerial capability

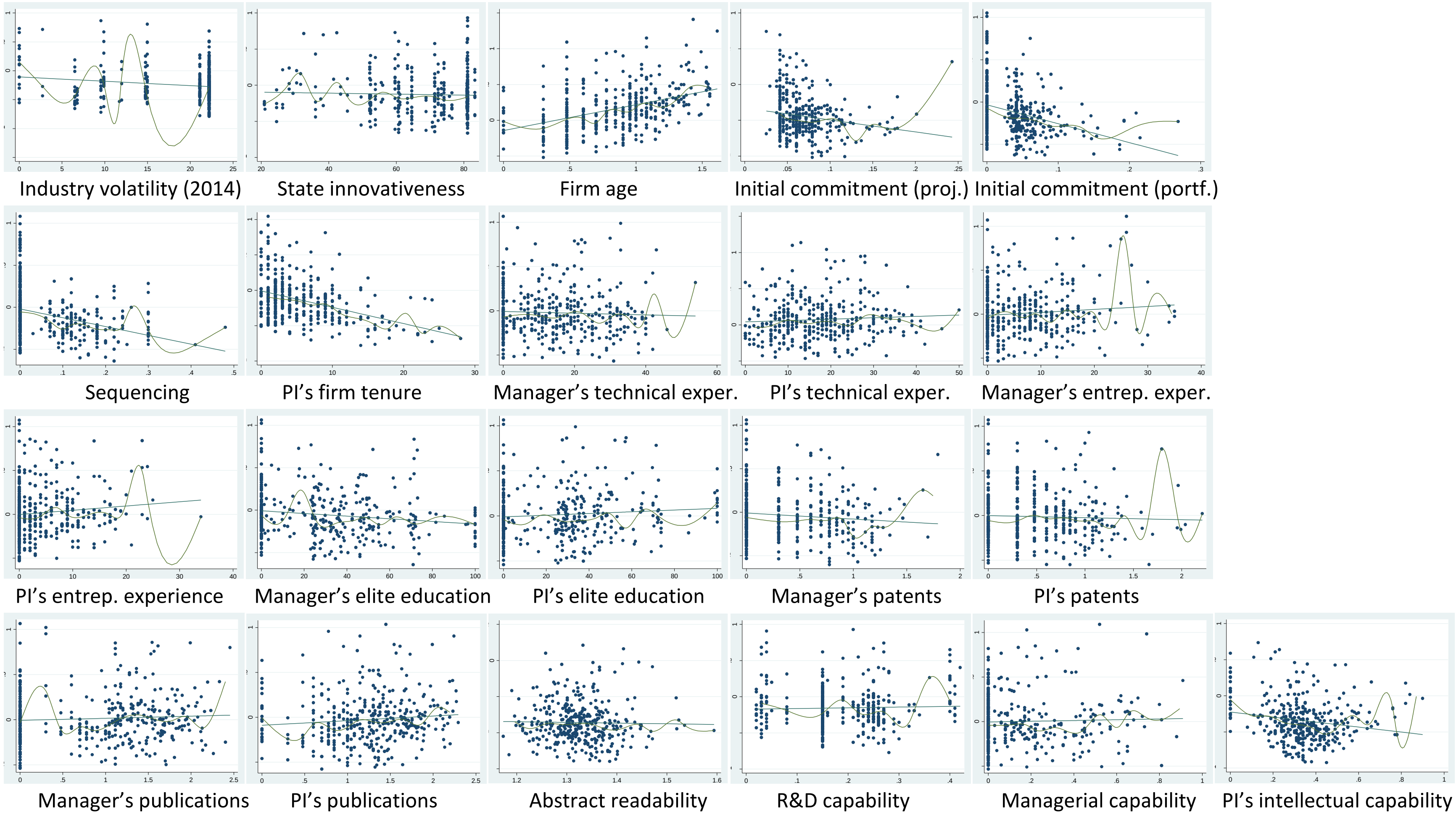

PI's intellectual capability


Initial commitment (portf.)

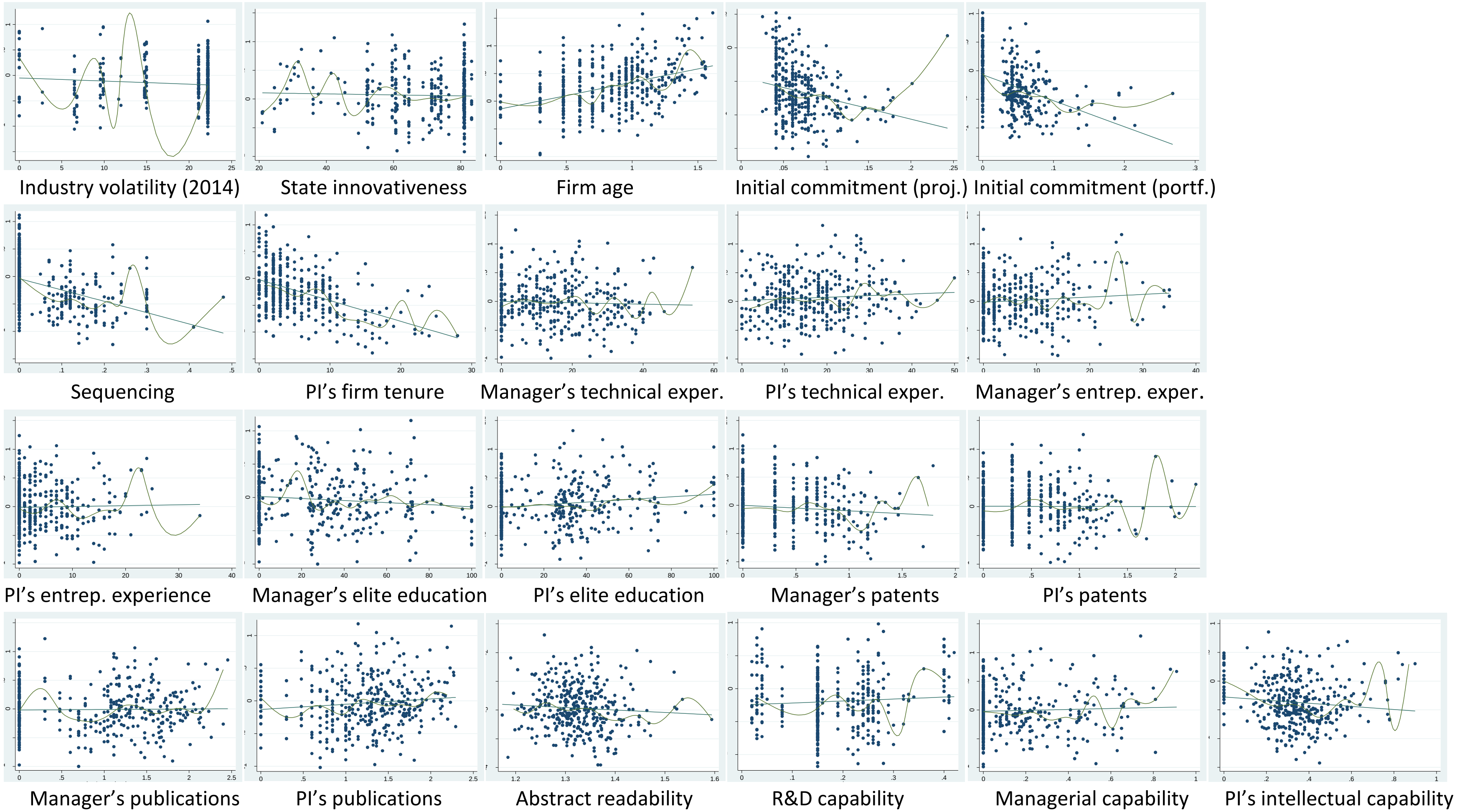

Sequencing

[43] Vertical axes depict the augmented component plus residual, horizontal axes depict the respective independent variable

DV: Sales Yield



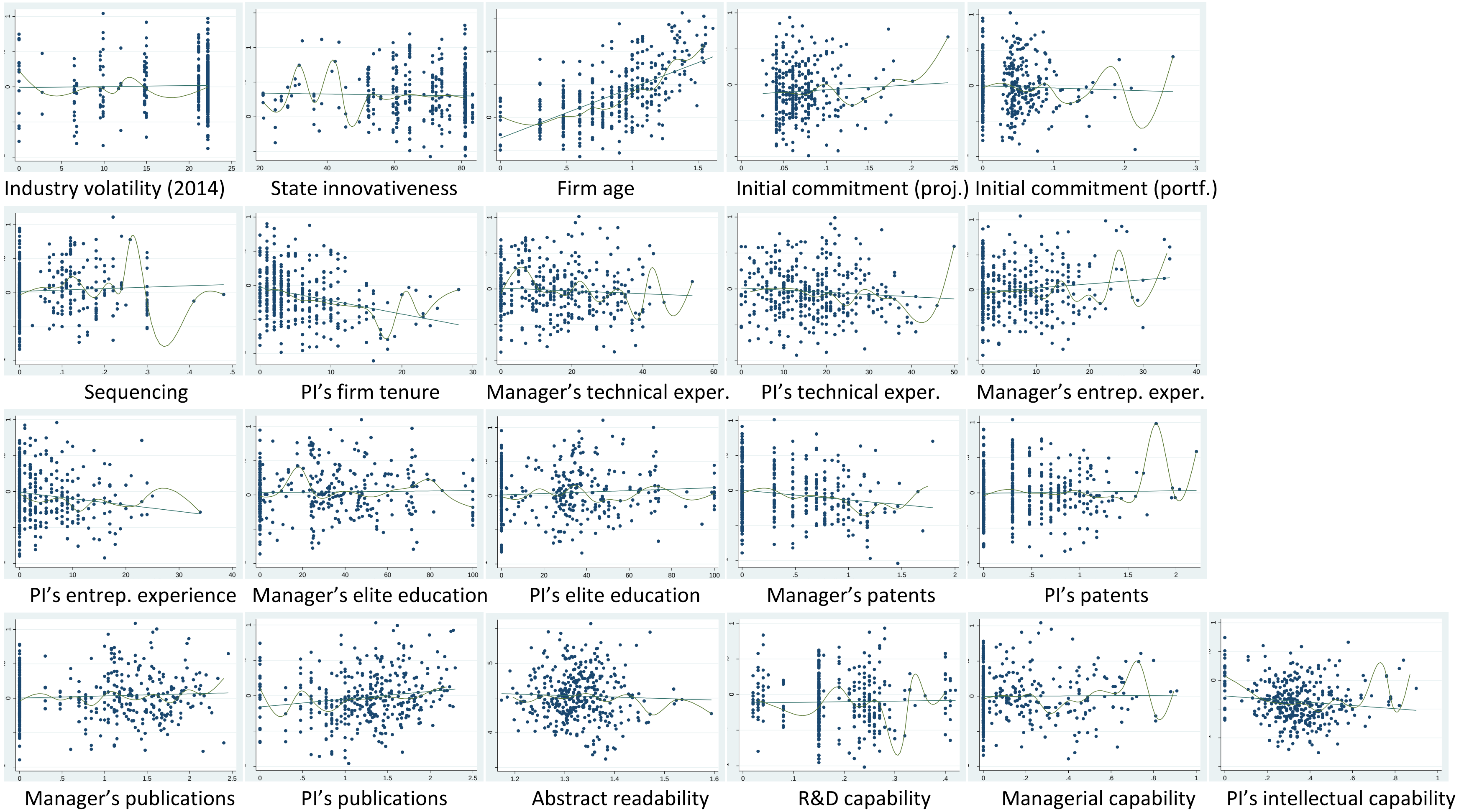
DV: Employment Yield



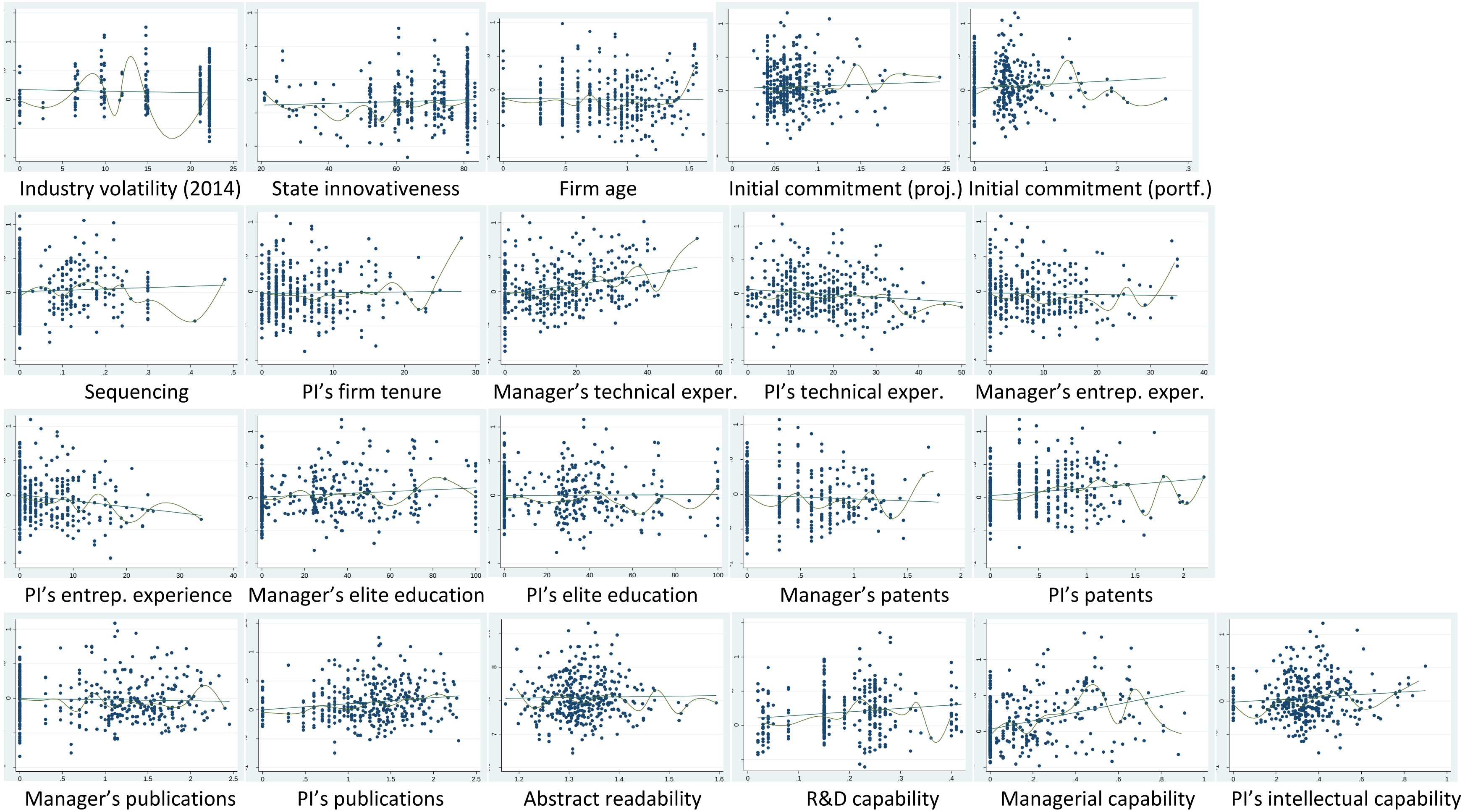
DV: Innovation Yield

DV: Sales Performance

DV: Employment Performance



DV: Innovation Performance

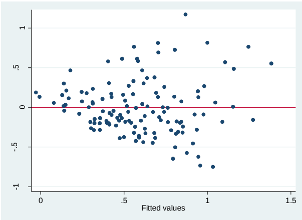


Appendix 20: Visual examination of data for homoscedasticity assumption – residuals-versus-fitted plots

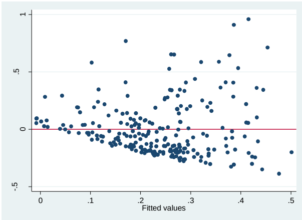
ROR Equations

DV: Sales Yield

no prior awards

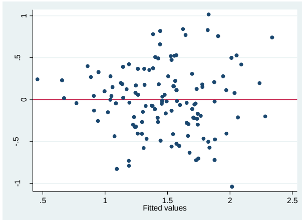


with prior awards

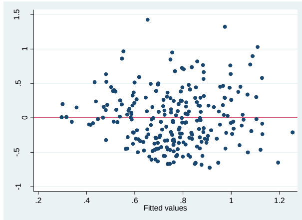


DV: Employment Yield

no prior awards

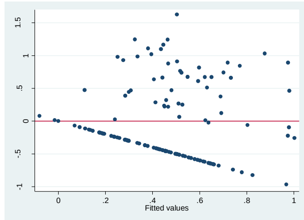


with prior awards

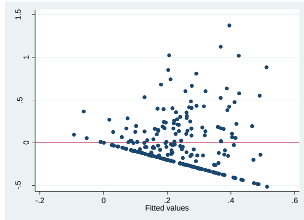


DV: Innovation Yield

no prior awards

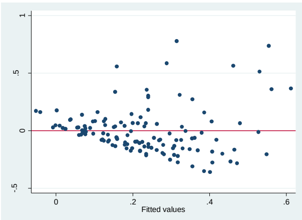


with prior awards

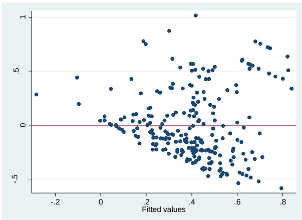


DV: Sales Performance

no prior awards

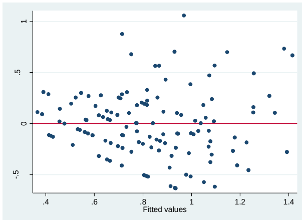


with prior awards

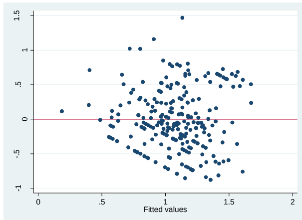


DV: Employment Performance

no prior awards

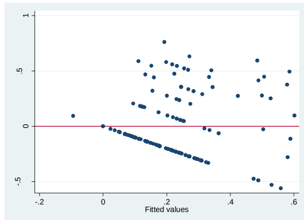


with prior awards

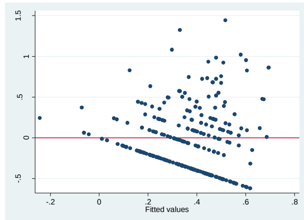


DV: Innovation Performance

no prior awards



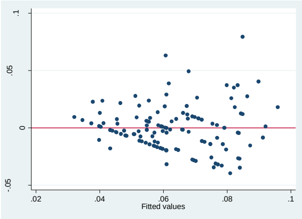
with prior awards



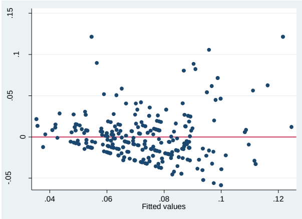
Signalling Equations

DV: Initial Commitment (project)

no prior awards

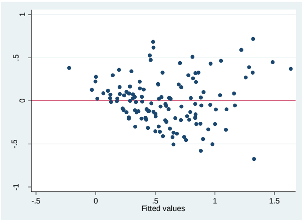


with prior awards

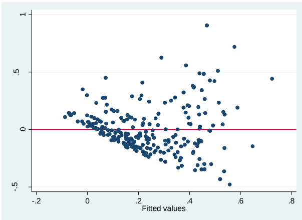


DV: Sales Yield

no prior awards

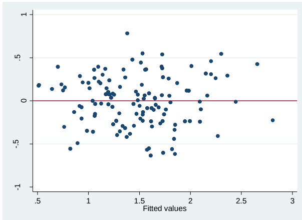


with prior awards

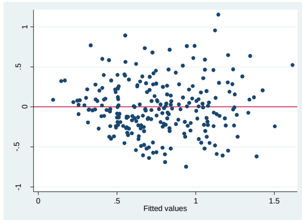


DV: Employment Yield

no prior awards

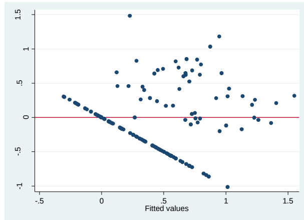


with prior awards

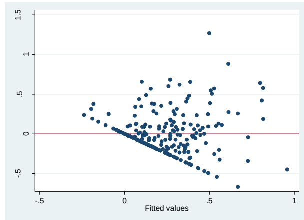


DV: Innovation Yield

no prior awards

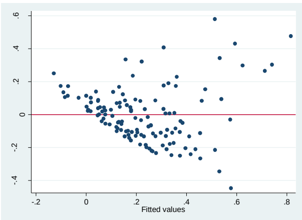


with prior awards

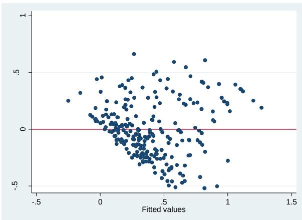


DV: Sales Performance

no prior awards

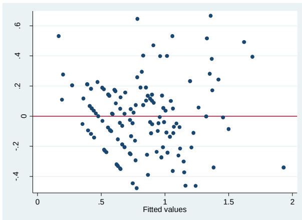


with prior awards

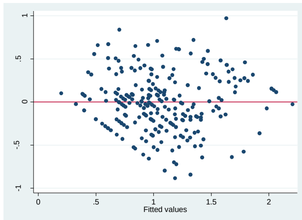


DV: Employment Performance

no prior awards

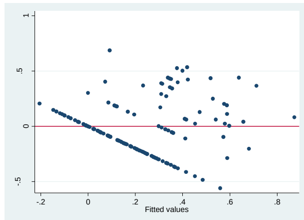


with prior awards

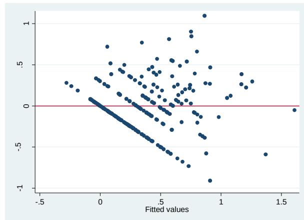


DV: Innovation Performance

no prior awards



with prior awards



Appendix 21: Multicollinearity diagnostics – variance inflation factor and conditional index

DV: Initial Commitment (project)

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
lnsuccessmagnitude	1.27	1.13	0.7861	0.2139
woman_owned	1.28	1.13	0.7783	0.2217
minority_owned	1.14	1.07	0.8741	0.1259
hubzone_owned	1.20	1.10	0.8320	0.1680
industryvolatility_5_year_wind	2.29	1.51	0.4372	0.5628
innovativeenvironment	1.27	1.13	0.7857	0.2143
lnfirmage	2.72	1.65	0.3681	0.6319
yeardummy	2.36	1.54	0.4238	0.5762
p1_position	1.71	1.31	0.5849	0.4151
p2_position	1.61	1.27	0.6209	0.3791
p2_firm_specificcapability	2.88	1.70	0.3469	0.6531
p1_technicalcapability	3.07	1.75	0.3253	0.6747
p2_technicalcapability	2.39	1.55	0.4178	0.5822
p1_entrepreneurialcapability	2.51	1.58	0.3985	0.6015
p2_entrepreneurialcapability	2.57	1.60	0.3893	0.6107
p1_eliteeducation_score	1.81	1.35	0.5519	0.4481
p2_eliteeducation_score	1.55	1.25	0.6437	0.3563
p1_mba_status	1.50	1.22	0.6689	0.3311
p2_mba_status	1.26	1.12	0.7963	0.2037
p1_dr_status	2.13	1.46	0.4684	0.5316
p2_dr_status	1.39	1.18	0.7181	0.2819
p1_academicposition_dummy	2.05	1.43	0.4882	0.5118
p2_academicposition_dummy	1.65	1.28	0.6070	0.3930
lnp1_intellectualcompetence	2.00	1.42	0.4989	0.5011
lnp2_intellectualcompetence	1.86	1.36	0.5375	0.4625
lnp1_academiccompetence	3.59	1.90	0.2783	0.7217
lnp2_academiccompetence	2.43	1.56	0.4113	0.5887
lnfogindex	1.23	1.11	0.8099	0.1901
rd_cap	1.23	1.11	0.8131	0.1869
managerial_cap	1.65	1.29	0.6044	0.3956
intellectual_cap	1.56	1.25	0.6403	0.3597
applicationbreadth	1.27	1.13	0.7891	0.2109
federalprogramtype	1.20	1.10	0.8310	0.1690
lnaveragephaseiprojectsuccess	1.39	1.18	0.7173	0.2827
lnphaseiitransitionrate	1.56	1.25	0.6402	0.3598
fit_firm_level	1.71	1.31	0.5851	0.4149
Mean VIF	1.84			

	Eigenval	Cond Index
1	4.3130	1.0000
2	3.0783	1.1837
3	2.1917	1.4028
4	2.0562	1.4483
5	1.8927	1.5095
6	1.6931	1.5961
7	1.5827	1.6508
8	1.5151	1.6872
9	1.2483	1.8588
10	1.2258	1.8758
11	1.1767	1.9145
12	1.0714	2.0064
13	1.0207	2.0556
14	0.9887	2.0886
15	0.9081	2.1793
16	0.8911	2.2000
17	0.7937	2.3310
18	0.7670	2.3713
19	0.7066	2.4706
20	0.6629	2.5507
21	0.6364	2.6033
22	0.6094	2.6604
23	0.5886	2.7069
24	0.5405	2.8249
25	0.4962	2.9481
26	0.4674	3.0378
27	0.4246	3.1873
28	0.3951	3.3038
29	0.3659	3.4332
30	0.3331	3.5983
31	0.3084	3.7397
32	0.2706	3.9923
33	0.2238	4.3901
34	0.2106	4.5257
35	0.1840	4.8413
36	0.1615	5.1685

Condition Number 5.1685
Eigenvalues & Cond Index computed from deviation sscp (no intercept)
Det(correlation matrix) 0.0000

DV: Discontinuation

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
success0failure1	1.26	1.12	0.7906	0.2094
woman_owned	1.31	1.14	0.7639	0.2361
minority_owned	1.16	1.07	0.8657	0.1343
hubzone_owned	1.24	1.12	0.8042	0.1958
industryvolatility_5_year_wind	2.34	1.53	0.4280	0.5720
innovativeenvironment	1.29	1.13	0.7774	0.2226
lnfirmage	2.74	1.66	0.3644	0.6356
yeardummy	2.41	1.55	0.4143	0.5857
p1_position	1.74	1.32	0.5740	0.4260
p2_position	1.68	1.30	0.5940	0.4060
p2_firm_specificcapability	2.92	1.71	0.3423	0.6577
p1_technicalcapability	3.10	1.76	0.3226	0.6774
p2_technicalcapability	2.47	1.57	0.4053	0.5947
p1_entrepreneurialcapability	2.54	1.59	0.3935	0.6065
p2_entrepreneurialcapability	2.58	1.61	0.3875	0.6125
p1_eliteeducation_score	1.84	1.36	0.5432	0.4568
p2_eliteeducation_score	1.57	1.25	0.6368	0.3632
p1_mba_status	1.53	1.24	0.6518	0.3482
p2_mba_status	1.26	1.12	0.7908	0.2092
p1_dr_status	2.15	1.47	0.4649	0.5351
p2_dr_status	1.41	1.19	0.7099	0.2901
p1_academicposition_dummy	2.06	1.43	0.4861	0.5139
p2_academicposition_dummy	1.67	1.29	0.5976	0.4024
lnp1_intellectualcompetence	2.04	1.43	0.4893	0.5107
lnp2_intellectualcompetence	1.94	1.39	0.5167	0.4833
lnp1_academiccompetence	3.62	1.90	0.2760	0.7240
lnp2_academiccompetence	2.44	1.56	0.4095	0.5905
projecttime	1.39	1.18	0.7170	0.2830
lnpostfundingrates_inventionacti	2.46	1.57	0.4072	0.5928
lnfogindex	1.24	1.11	0.8075	0.1925
rd_cap	1.36	1.17	0.7365	0.2635
managerial_cap	2.34	1.53	0.4280	0.5720
intellectual_cap	1.57	1.25	0.6386	0.3614
applicationbreadth	1.28	1.13	0.7824	0.2176
federalprogramtype	1.22	1.10	0.8196	0.1804
lnsuccessmagnitude	1.37	1.17	0.7302	0.2698
lnaveragephaseiprojectsuccess	1.41	1.19	0.7115	0.2885
lnphaseiitransitionrate	1.60	1.26	0.6261	0.3739
fit_firm_level	1.71	1.31	0.5832	0.4168
Mean VIF	1.88			

	Eigenval	Cond Index
1	4.3211	1.0000
2	3.3396	1.1375
3	2.4563	1.3263
4	2.1158	1.4291
5	1.9811	1.4769
6	1.8022	1.5484
7	1.6263	1.6300
8	1.5930	1.6470
9	1.4072	1.7523
10	1.2368	1.8692
11	1.2095	1.8901
12	1.0929	1.9884
13	1.0619	2.0172
14	1.0148	2.0635
15	0.9732	2.1072
16	0.9204	2.1667
17	0.8488	2.2563
18	0.8222	2.2925
19	0.7793	2.3547
20	0.7449	2.4084
21	0.6750	2.5302
22	0.6588	2.5611
23	0.6282	2.6226
24	0.5910	2.7039
25	0.5552	2.7897
26	0.5048	2.9259
27	0.4879	2.9759
28	0.4663	3.0440
29	0.4131	3.2344
30	0.3920	3.3203
31	0.3519	3.5042
32	0.3287	3.6257
33	0.3096	3.7361
34	0.2771	3.9488
35	0.2509	4.1502
36	0.2168	4.4644
37	0.2051	4.5900
38	0.1815	4.8787
39	0.1588	5.2159

Condition Number 5.2159

Eigenvalues & Cond Index computed from deviation sscp (no intercept)

Det(correlation matrix) 0.0000

DV: Sales Yield

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
lnsalesyield	1.79	1.34	0.5586	0.4414
woman_owned	1.35	1.16	0.7409	0.2591
minority_owned	1.16	1.08	0.8650	0.1350
hubzone_owned	1.25	1.12	0.7972	0.2028
industryvolatility_5_year_2013	1.33	1.15	0.7530	0.2470
innovativeenvironment	1.33	1.15	0.7530	0.2470
lnfirmage	2.97	1.72	0.3362	0.6638
yeardummy	1.32	1.15	0.7561	0.2439
lnsuccessmagnitude	1.39	1.18	0.7217	0.2783
success0failure1	1.34	1.16	0.7468	0.2532
fit_project_level	1.18	1.09	0.8441	0.1559
lnaveragephaseiprojectsuccess	1.54	1.24	0.6493	0.3507
lnphaseiitransitionrate	1.69	1.30	0.5925	0.4075
fit_firm_level	1.80	1.34	0.5569	0.4431
p1_position	1.75	1.32	0.5723	0.4277
p2_position	1.68	1.30	0.5947	0.4053
p2_firm_specificcapability	3.10	1.76	0.3229	0.6771
p1_technicalcapability	3.09	1.76	0.3238	0.6762
p2_technicalcapability	2.44	1.56	0.4106	0.5894
p1_entrepreneurialcapability	2.59	1.61	0.3856	0.6144
p2_entrepreneurialcapability	2.63	1.62	0.3806	0.6194
p1_eliteeducation_score	1.86	1.36	0.5367	0.4633
p2_eliteeducation_score	1.54	1.24	0.6487	0.3513
p1_mba_status	1.61	1.27	0.6206	0.3794
p2_mba_status	1.27	1.13	0.7867	0.2133
p1_dr_status	2.21	1.49	0.4516	0.5484
p2_dr_status	1.42	1.19	0.7035	0.2965
p1_academicposition_dummy	2.08	1.44	0.4800	0.5200
p2_academicposition_dummy	1.70	1.30	0.5872	0.4128
lnp1_intellectualcompetence	2.09	1.45	0.4774	0.5226
lnp2_intellectualcompetence	1.96	1.40	0.5090	0.4910
lnp1_academiccompetence	3.67	1.91	0.2727	0.7273
lnp2_academiccompetence	2.49	1.58	0.4011	0.5989
projecttime	1.40	1.18	0.7152	0.2848
lnpostfundingrates_inventionacti	2.52	1.59	0.3971	0.6029
lnfogindex	1.24	1.11	0.8070	0.1930
rd_cap	1.45	1.21	0.6875	0.3125
managerial_cap	2.95	1.72	0.3396	0.6604
intellectual_cap	1.69	1.30	0.5904	0.4096
rdcapxmancap	1.65	1.28	0.6065	0.3935
rdcapxintcap	1.22	1.10	0.8201	0.1799
intcapxmancap	1.29	1.14	0.7735	0.2265
Mean VIF	1.86			

	Eigenval	Cond Index
1	4.3546	1.0000
2	3.4550	1.1227
3	2.5082	1.3176
4	2.2921	1.3783
5	2.0250	1.4664
6	1.6974	1.6017
7	1.6162	1.6415
8	1.4956	1.7063
9	1.4486	1.7338
10	1.2972	1.8322
11	1.2594	1.8595
12	1.1382	1.9560
13	1.1190	1.9727
14	1.0999	1.9897
15	1.0491	2.0374
16	1.0342	2.0520
17	0.9666	2.1226
18	0.8928	2.2085
19	0.8201	2.3043
20	0.7879	2.3510
21	0.7661	2.3842
22	0.7036	2.4878
23	0.6816	2.5277
24	0.6581	2.5723
25	0.6382	2.6121
26	0.5866	2.7245
27	0.5751	2.7518
28	0.5264	2.8761
29	0.5043	2.9385
30	0.4809	3.0092
31	0.4639	3.0638
32	0.4302	3.1816
33	0.3798	3.3861
34	0.3463	3.5459
35	0.3268	3.6502
36	0.3147	3.7196
37	0.2821	3.9292
38	0.2595	4.0961
39	0.2045	4.6140
40	0.1890	4.7999
41	0.1692	5.0734
42	0.1560	5.2830

Condition Number 5.2830

Eigenvalues & Cond Index computed from deviation sscp (no intercept)

Det(correlation matrix) 0.0000

DV: Employment Yield

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
lnemploymentyield	2.24	1.50	0.4473	0.5527
woman_owned	1.34	1.16	0.7471	0.2529
minority_owned	1.16	1.08	0.8636	0.1364
hubzone_owned	1.25	1.12	0.8003	0.1997
industryvolatility_5_year_2013	1.31	1.14	0.7652	0.2348
innovativeenvironment	1.33	1.15	0.7532	0.2468
lnfirmage	2.98	1.72	0.3361	0.6639
yeardummy	1.32	1.15	0.7549	0.2451
lnsuccessmagnitude	1.41	1.19	0.7098	0.2902
success0failure1	1.34	1.16	0.7460	0.2540
fit_project_level	1.19	1.09	0.8438	0.1562
lnaveragephaseiprojectsuccess	1.64	1.28	0.6097	0.3903
lnphaseiitransitionrate	1.78	1.33	0.5622	0.4378
fit_firm_level	1.80	1.34	0.5546	0.4454
p1_position	1.75	1.32	0.5713	0.4287
p2_position	1.69	1.30	0.5921	0.4079
p2_firm_specificcapability	3.18	1.78	0.3146	0.6854
p1_technicalcapability	3.09	1.76	0.3238	0.6762
p2_technicalcapability	2.44	1.56	0.4106	0.5894
p1_entrepreneurialcapability	2.59	1.61	0.3858	0.6142
p2_entrepreneurialcapability	2.62	1.62	0.3816	0.6184
p1_eliteeducation_score	1.85	1.36	0.5400	0.4600
p2_eliteeducation_score	1.56	1.25	0.6422	0.3578
p1_mba_status	1.62	1.27	0.6186	0.3814
p2_mba_status	1.28	1.13	0.7807	0.2193
p1_dr_status	2.23	1.49	0.4478	0.5522
p2_dr_status	1.42	1.19	0.7024	0.2976
p1_academicposition_dummy	2.09	1.44	0.4794	0.5206
p2_academicposition_dummy	1.70	1.30	0.5876	0.4124
lnp1_intellectualcompetence	2.10	1.45	0.4772	0.5228
lnp2_intellectualcompetence	1.96	1.40	0.5094	0.4906
lnp1_academiccompetence	3.67	1.91	0.2728	0.7272
lnp2_academiccompetence	2.50	1.58	0.4006	0.5994
projecttime	1.42	1.19	0.7045	0.2955
lnpostfundingrates_inventionacti	2.49	1.58	0.4014	0.5986
lnfogindex	1.24	1.11	0.8049	0.1951
rd_cap	1.46	1.21	0.6867	0.3133
managerial_cap	2.95	1.72	0.3394	0.6606
intellectual_cap	1.69	1.30	0.5925	0.4075
rdcapxmancap	1.65	1.28	0.6066	0.3934
rdcapxintcap	1.22	1.11	0.8185	0.1815
intcapxmancap	1.30	1.14	0.7699	0.2301
Mean VIF	1.88			

	Eigenval	Cond Index
1	4.3888	1.0000
2	3.4913	1.1212
3	2.5002	1.3249
4	2.3656	1.3621
5	2.0153	1.4757
6	1.6823	1.6152
7	1.6015	1.6554
8	1.5021	1.7093
9	1.4484	1.7407
10	1.2981	1.8388
11	1.2505	1.8734
12	1.1386	1.9633
13	1.1177	1.9816
14	1.0971	2.0001
15	1.0514	2.0431
16	1.0344	2.0598
17	0.9674	2.1300
18	0.8922	2.2179
19	0.8124	2.3244
20	0.7852	2.3642
21	0.7582	2.4060
22	0.7039	2.4970
23	0.6822	2.5363
24	0.6596	2.5795
25	0.6274	2.6448
26	0.5877	2.7328
27	0.5760	2.7605
28	0.5268	2.8863
29	0.5048	2.9485
30	0.4835	3.0130
31	0.4583	3.0944
32	0.3960	3.3292
33	0.3718	3.4358
34	0.3401	3.5921
35	0.3259	3.6699
36	0.3037	3.8016
37	0.2819	3.9458
38	0.2613	4.0985
39	0.2029	4.6505
40	0.1890	4.8184
41	0.1647	5.1618
42	0.1537	5.3443

Condition Number 5.3443

Eigenvalues & Cond Index computed from deviation sscp (no intercept)

Det(correlation matrix) 0.0000

DV: Innovation Yield

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
lninnovationyield	1.39	1.18	0.7201	0.2799
woman_owned	1.29	1.13	0.7764	0.2236
minority_owned	1.14	1.07	0.8737	0.1263
hubzone_owned	1.23	1.11	0.8125	0.1875
industryvolatility_5_year_2013	1.28	1.13	0.7790	0.2210
innovativeenvironment	1.32	1.15	0.7558	0.2442
lnfirmage	2.82	1.68	0.3552	0.6448
yeardummy	1.33	1.15	0.7499	0.2501
lnsuccessmagnitude	1.36	1.17	0.7353	0.2647
success0failure1	1.33	1.15	0.7513	0.2487
fit_project_level	1.18	1.09	0.8460	0.1540
lnaveragephaseiprojectsuccess	1.47	1.21	0.6812	0.3188
lnphaseiitransitionrate	1.60	1.27	0.6238	0.3762
fit_firm_level	1.74	1.32	0.5759	0.4241
p1_position	1.74	1.32	0.5753	0.4247
p2_position	1.68	1.30	0.5948	0.4052
p2_firm_specificcapability	2.93	1.71	0.3416	0.6584
p1_technicalcapability	3.10	1.76	0.3223	0.6777
p2_technicalcapability	2.41	1.55	0.4154	0.5846
p1_entrepreneurialcapability	2.59	1.61	0.3860	0.6140
p2_entrepreneurialcapability	2.62	1.62	0.3820	0.6180
p1_eliteeducation_score	1.82	1.35	0.5508	0.4492
p2_eliteeducation_score	1.53	1.24	0.6549	0.3451
p1_mba_status	1.57	1.25	0.6355	0.3645
p2_mba_status	1.25	1.12	0.7998	0.2002
p1_dr_status	2.19	1.48	0.4557	0.5443
p2_dr_status	1.41	1.19	0.7106	0.2894
p1_academicposition_dummy	2.07	1.44	0.4830	0.5170
p2_academicposition_dummy	1.72	1.31	0.5811	0.4189
lnp1_intellectualcompetence	2.07	1.44	0.4823	0.5177
lnp2_intellectualcompetence	1.92	1.38	0.5217	0.4783
lnp1_academiccompetence	3.67	1.92	0.2726	0.7274
lnp2_academiccompetence	2.50	1.58	0.3998	0.6002
projecttime	1.40	1.18	0.7142	0.2858
lnfogindex	1.24	1.11	0.8087	0.1913
rd_cap	1.36	1.17	0.7363	0.2637
managerial_cap	2.33	1.53	0.4290	0.5710
intellectual_cap	1.70	1.30	0.5872	0.4128
rdcapxmancap	1.65	1.28	0.6074	0.3926
rdcapxintcap	1.22	1.10	0.8197	0.1803
intcapxmancap	1.29	1.13	0.7781	0.2219
Mean VIF	1.79			

	Eigenval	Cond Index
1	4.3728	1.0000
2	3.1631	1.1758
3	2.4296	1.3416
4	2.2291	1.4006
5	1.9412	1.5009
6	1.6743	1.6161
7	1.4906	1.7127
8	1.4774	1.7204
9	1.4224	1.7534
10	1.2819	1.8470
11	1.2236	1.8904
12	1.1358	1.9621
13	1.0992	1.9946
14	1.0932	2.0000
15	1.0437	2.0469
16	1.0182	2.0723
17	0.9695	2.1237
18	0.9022	2.2015
19	0.8057	2.3297
20	0.7928	2.3485
21	0.7507	2.4134
22	0.7159	2.4715
23	0.6839	2.5286
24	0.6666	2.5612
25	0.6157	2.6649
26	0.5987	2.7025
27	0.5666	2.7780
28	0.5297	2.8731
29	0.5059	2.9401
30	0.4850	3.0027
31	0.4691	3.0531
32	0.4460	3.1313
33	0.3828	3.3796
34	0.3485	3.5420
35	0.3254	3.6658
36	0.3161	3.7193
37	0.2796	3.9546
38	0.2097	4.5669
39	0.1962	4.7212
40	0.1844	4.8702
41	0.1571	5.2754

Condition Number 5.2754

Eigenvalues & Cond Index computed from deviation sscp (no intercept)

Det(correlation matrix) 0.0000

DV: Sales Performance

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
lnsales	1.88	1.37	0.5310	0.4690
woman_owned	1.32	1.15	0.7564	0.2436
minority_owned	1.15	1.07	0.8733	0.1267
hubzone_owned	1.24	1.12	0.8037	0.1963
industryvolatility_5_year_2013	1.27	1.13	0.7878	0.2122
innovativeenvironment	1.30	1.14	0.7670	0.2330
lnfirmage	2.94	1.71	0.3405	0.6595
yeardummy	1.31	1.14	0.7645	0.2355
lnsuccessmagnitude	1.30	1.14	0.7667	0.2333
success0failure1	1.33	1.15	0.7545	0.2455
fit_project_level	1.18	1.08	0.8505	0.1495
p1_position	1.76	1.33	0.5680	0.4320
p2_position	1.67	1.29	0.5985	0.4015
p2_firm_specificcapability	2.90	1.70	0.3444	0.6556
p1_technicalcapability	3.08	1.76	0.3247	0.6753
p2_technicalcapability	2.38	1.54	0.4197	0.5803
p1_entrepreneurialcapability	2.60	1.61	0.3845	0.6155
p2_entrepreneurialcapability	2.65	1.63	0.3774	0.6226
p1_eliteeducation_score	1.80	1.34	0.5565	0.4435
p2_eliteeducation_score	1.53	1.24	0.6551	0.3449
p1_mba_status	1.54	1.24	0.6499	0.3501
p2_mba_status	1.25	1.12	0.7997	0.2003
p1_dr_status	2.20	1.48	0.4555	0.5445
p2_dr_status	1.42	1.19	0.7050	0.2950
p1_academicposition_dummy	2.05	1.43	0.4869	0.5131
p2_academicposition_dummy	1.70	1.30	0.5890	0.4110
lnp1_intellectualcompetence	2.07	1.44	0.4840	0.5160
lnp2_intellectualcompetence	1.94	1.39	0.5168	0.4832
lnp1_academiccompetence	3.64	1.91	0.2748	0.7252
lnp2_academiccompetence	2.48	1.57	0.4040	0.5960
projecttime	1.39	1.18	0.7213	0.2787
lnpostfundingrates_inventionacti	2.67	1.63	0.3749	0.6251
lnfogindex	1.23	1.11	0.8098	0.1902
rd_cap	1.44	1.20	0.6964	0.3036
managerial_cap	2.91	1.71	0.3432	0.6568
intellectual_cap	1.69	1.30	0.5934	0.4066
rdcapxmancap	1.61	1.27	0.6210	0.3790
rdcapxintcap	1.21	1.10	0.8274	0.1726
intcapxmancap	1.29	1.14	0.7738	0.2262
Mean VIF	1.85			

	Eigenval	Cond Index
1	4.2797	1.0000
2	3.4200	1.1186
3	2.4697	1.3164
4	2.0752	1.4361
5	1.8178	1.5344
6	1.6538	1.6087
7	1.5365	1.6689
8	1.4666	1.7083
9	1.3066	1.8099
10	1.2530	1.8482
11	1.1788	1.9054
12	1.1476	1.9311
13	1.0891	1.9823
14	1.0592	2.0101
15	1.0235	2.0448
16	0.9734	2.0968
17	0.9208	2.1559
18	0.8161	2.2900
19	0.7939	2.3218
20	0.7773	2.3465
21	0.6868	2.4963
22	0.6726	2.5225
23	0.6553	2.5556
24	0.6238	2.6194
25	0.5844	2.7060
26	0.5491	2.7919
27	0.5175	2.8757
28	0.4931	2.9460
29	0.4645	3.0354
30	0.3842	3.3375
31	0.3597	3.4493
32	0.3455	3.5193
33	0.3259	3.6238
34	0.2887	3.8499
35	0.2508	4.1307
36	0.2128	4.4848
37	0.1917	4.7247
38	0.1726	4.9799
39	0.1622	5.1361

Condition Number 5.1361

Eigenvalues & Cond Index computed from deviation sscp (no intercept)

Det(correlation matrix) 0.0000

DV: Employment Performance

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
lnemployees	1.95	1.40	0.5125	0.4875
woman_owned	1.32	1.15	0.7556	0.2444
minority_owned	1.14	1.07	0.8742	0.1258
hubzone_owned	1.24	1.11	0.8069	0.1931
industryvolatility_5_year_2013	1.27	1.13	0.7880	0.2120
innovativeenvironment	1.30	1.14	0.7672	0.2328
lnfirmage	3.03	1.74	0.3298	0.6702
yeardummy	1.33	1.15	0.7545	0.2455
lnsuccessmagnitude	1.30	1.14	0.7680	0.2320
success0failure1	1.32	1.15	0.7558	0.2442
fit_project_level	1.18	1.08	0.8502	0.1498
p1_position	1.77	1.33	0.5658	0.4342
p2_position	1.67	1.29	0.5983	0.4017
p2_firm_specificcapability	2.92	1.71	0.3430	0.6570
p1_technicalcapability	3.08	1.76	0.3243	0.6757
p2_technicalcapability	2.39	1.55	0.4187	0.5813
p1_entrepreneurialcapability	2.60	1.61	0.3849	0.6151
p2_entrepreneurialcapability	2.64	1.63	0.3782	0.6218
p1_eliteeducation_score	1.80	1.34	0.5563	0.4437
p2_eliteeducation_score	1.53	1.24	0.6530	0.3470
p1_mba_status	1.54	1.24	0.6478	0.3522
p2_mba_status	1.25	1.12	0.7991	0.2009
p1_dr_status	2.20	1.48	0.4537	0.5463
p2_dr_status	1.42	1.19	0.7026	0.2974
p1_academicposition_dummy	2.05	1.43	0.4875	0.5125
p2_academicposition_dummy	1.70	1.30	0.5893	0.4107
lnp1_intellectualcompetence	2.05	1.43	0.4867	0.5133
lnp2_intellectualcompetence	1.93	1.39	0.5174	0.4826
lnp1_academiccompetence	3.64	1.91	0.2749	0.7251
lnp2_academiccompetence	2.48	1.58	0.4027	0.5973
projecttime	1.40	1.18	0.7161	0.2839
lnpostfundingrates_inventionacti	2.59	1.61	0.3858	0.6142
lnfogindex	1.24	1.11	0.8091	0.1909
rd_cap	1.43	1.20	0.6972	0.3028
managerial_cap	2.91	1.71	0.3436	0.6564
intellectual_cap	1.69	1.30	0.5934	0.4066
rdcapxmancap	1.61	1.27	0.6217	0.3783
rdcapxintcap	1.21	1.10	0.8247	0.1753
intcapxmancap	1.28	1.13	0.7782	0.2218
Mean VIF	1.86			

	Eigenval	Cond Index
1	4.2844	1.0000
2	3.4646	1.1120
3	2.4722	1.3164
4	2.0706	1.4385
5	1.7865	1.5486
6	1.6545	1.6092
7	1.5229	1.6773
8	1.4701	1.7071
9	1.3087	1.8093
10	1.2531	1.8491
11	1.1722	1.9118
12	1.1454	1.9340
13	1.0856	1.9866
14	1.0601	2.0104
15	1.0242	2.0453
16	0.9746	2.0967
17	0.9205	2.1574
18	0.8069	2.3043
19	0.7847	2.3367
20	0.7750	2.3512
21	0.7011	2.4721
22	0.6861	2.4990
23	0.6552	2.5572
24	0.6230	2.6225
25	0.5842	2.7080
26	0.5596	2.7669
27	0.5149	2.8846
28	0.4929	2.9484
29	0.4716	3.0141
30	0.3815	3.3512
31	0.3496	3.5005
32	0.3399	3.5505
33	0.3225	3.6448
34	0.2892	3.8487
35	0.2566	4.0861
36	0.2098	4.5192
37	0.1921	4.7227
38	0.1709	5.0066
39	0.1623	5.1384

Condition Number 5.1384

Eigenvalues & Cond Index computed from deviation sscp (no intercept)

Det(correlation matrix) 0.0000

DV: Innovation Performance

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
lninnovationperformance	1.62	1.27	0.6161	0.3839
woman_owned	1.28	1.13	0.7799	0.2201
minority_owned	1.13	1.06	0.8827	0.1173
hubzone_owned	1.22	1.11	0.8178	0.1822
industryvolatility_5_year_2013	1.26	1.12	0.7934	0.2066
innovativeenvironment	1.30	1.14	0.7680	0.2320
lnfirmage	2.54	1.59	0.3944	0.6056
yeardummy	1.33	1.15	0.7497	0.2503
lnsuccessmagnitude	1.30	1.14	0.7687	0.2313
success0failure1	1.32	1.15	0.7564	0.2436
fit_project_level	1.17	1.08	0.8522	0.1478
p1_position	1.72	1.31	0.5799	0.4201
p2_position	1.67	1.29	0.5972	0.4028
p2_firm_specificcapability	2.85	1.69	0.3511	0.6489
p1_technicalcapability	3.15	1.78	0.3172	0.6828
p2_technicalcapability	2.38	1.54	0.4205	0.5795
p1_entrepreneurialcapability	2.58	1.61	0.3875	0.6125
p2_entrepreneurialcapability	2.64	1.62	0.3792	0.6208
p1_eliteeducation_score	1.78	1.33	0.5616	0.4384
p2_eliteeducation_score	1.52	1.23	0.6597	0.3403
p1_mba_status	1.55	1.25	0.6445	0.3555
p2_mba_status	1.25	1.12	0.8006	0.1994
p1_dr_status	2.19	1.48	0.4572	0.5428
p2_dr_status	1.40	1.18	0.7134	0.2866
p1_academicposition_dummy	2.04	1.43	0.4903	0.5097
p2_academicposition_dummy	1.69	1.30	0.5902	0.4098
lnp1_intellectualcompetence	2.01	1.42	0.4973	0.5027
lnp2_intellectualcompetence	1.91	1.38	0.5238	0.4762
lnp1_academiccompetence	3.62	1.90	0.2762	0.7238
lnp2_academiccompetence	2.48	1.58	0.4030	0.5970
projecttime	1.38	1.18	0.7225	0.2775
lnfogindex	1.23	1.11	0.8108	0.1892
rd_cap	1.36	1.17	0.7343	0.2657
managerial_cap	2.41	1.55	0.4146	0.5854
intellectual_cap	1.70	1.30	0.5899	0.4101
rdcapxmancap	1.61	1.27	0.6224	0.3776
rdcapxintcap	1.21	1.10	0.8250	0.1750
intcapxmancap	1.28	1.13	0.7796	0.2204
Mean VIF	1.79			

	Eigenval	Cond Index
1	4.2688	1.0000
2	2.9706	1.1988
3	2.4878	1.3099
4	2.0592	1.4398
5	1.7768	1.5500
6	1.6379	1.6144
7	1.4898	1.6928
8	1.4356	1.7244
9	1.2786	1.8272
10	1.2390	1.8562
11	1.1639	1.9151
12	1.1408	1.9345
13	1.0780	1.9900
14	1.0654	2.0017
15	0.9950	2.0713
16	0.9724	2.0952
17	0.9340	2.1378
18	0.8095	2.2965
19	0.7855	2.3312
20	0.7569	2.3749
21	0.6915	2.4846
22	0.6726	2.5193
23	0.6522	2.5585
24	0.6346	2.5937
25	0.5745	2.7260
26	0.5160	2.8764
27	0.5066	2.9028
28	0.4803	2.9812
29	0.4403	3.1136
30	0.4118	3.2196
31	0.3649	3.4201
32	0.3389	3.5491
33	0.3174	3.6675
34	0.2910	3.8304
35	0.2168	4.4376
36	0.1980	4.6429
37	0.1856	4.7964
38	0.1617	5.1379

Condition Number 5.1379

Eigenvalues & Cond Index computed from deviation sscp (no intercept)

Det(correlation matrix) 0.0000

Appendix 22: Robustness check – system of equations (SUEST) results – full sample

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level constructs												
Initial commitment	-0.19	-2.92***	-0.24	-3.72***	-0.06	-1.22	0.08	1.49	0.05	0.99	0.05	0.83
Discontinuation	-0.06	-0.56	-0.06	-0.53	-0.16	-1.48	0.02	0.15	-0.03	-0.29	-0.20	-1.86*
Fit	-0.11	-1.05	-0.13	-1.29	-0.02	-0.23	-0.08	-0.75	-0.09	-0.93	-0.02	-0.18
Portfolio-level constructs												
Fit	0.28	2.59***	0.31	2.92***	0.14	1.44	-0.03	-0.32	-0.01	-0.08	0.12	1.09
Control variables:												
Non-woman-owned	0.45	1.58	0.46	2.03*	0.20	1.12	0.27	1.10	0.40	1.77*	0.25	1.49
Non-minority-owned	-0.11	-0.31	-0.23	-0.86	0.38	2.26**	0.06	0.20	0.01	0.02	0.57	3.79***
Non-HubZone-owned	-0.41	-1.25	-0.52	-1.66	-0.18	-0.65	-0.05	-0.21	-0.11	-0.42	0.12	0.59
Industry volatility	-0.21	-2.20***	-0.12	-1.44	0.03	0.38	-0.04	-0.52	0.05	0.65	0.06	0.95
State innovativeness	-0.05	-0.89	-0.06	-1.06	0.04	0.70	0.02	0.53	0.03	0.72	0.12	2.64***
Firm age	0.02	0.30	-0.11	-1.94*	-0.18	-3.05***	0.46	8.84***	0.47	9.63***	0.13	2.21**
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.12		0.15		0.09		0.26		0.29		0.12	
Adjusted R^2	0.08		0.12		0.05		0.23		0.23		0.08	

N= 367

*** p<0.01; ** p<0.05; * p<0.1

Appendix 23: Robustness check – system of equations (SUEST) results – cluster with no prior awards

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level constructs												
Initial commitment	-0.43	-4.05***	-0.41	-4.92***	-0.09	-0.65	-0.14	-2.11**	-0.19	-2.50**	0.01	0.10
Discontinuation	-0.35	-1.93*	-0.27	-1.81*	-0.50	-2.00**	-0.18	-1.52	-0.25	-1.74*	-0.26	-1.67
Fit	0.21	1.24	0.22	1.66	0.13	0.54	0.12	0.98	0.20	1.45	0.05	0.34
Control variables:												
Non-woman-owned	0.46	1.17	0.68	2.40**	0.00	0.00	0.17	0.51	0.59	3.95***	-0.07	-0.20
Non-minority-owned	-0.08	-0.12	-0.24	-0.57	0.80	1.78*	0.09	0.26	-0.01	-0.04	0.55	2.03**
Non-HubZone-owned	-0.11	-0.25	-0.20	-0.56	-0.26	-0.56	-0.10	-0.35	-0.26	-0.79	-0.12	-0.46
Industry volatility	-0.21	-1.14	-0.06	-0.45	0.10	0.71	-0.12	-1.09	-0.01	-0.07	0.09	1.00
State innovativeness	0.03	0.24	0.02	0.24	0.08	0.59	0.02	0.25	0.01	0.17	0.05	0.73
Firm age	0.49	4.04***	0.37	4.17***	-0.06	-0.45	0.30	3.53***	0.36	4.09***	-0.01	-0.09
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.37		0.41		0.13		0.29		0.33		0.19	
Adjusted R^2	0.28		0.33		0.01		0.20		0.24		0.08	

N= 128

*** p<0.01; ** p<0.05; * p<0.1

Appendix 24: Robustness check – system of equations (SUEST) results – cluster with prior awards

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level constructs	-0.03	-0.49	-0.08	-1.31	-0.02	-0.32	0.15	2.44**	0.13	2.16**	0.05	0.76
Initial commitment	0.07	0.67	0.03	0.29	-0.02	-0.22	0.06	0.39	0.00	0.03	-0.21	-1.46
Discontinuation	-0.02	-0.17	-0.07	-0.68	0.01	0.12	-0.18	-1.40	-0.23	-1.87*	-0.04	-0.30
Fit												
Portfolio-level constructs												
Initial commitment	-0.13	-2.43**	-0.15	-2.59**	-0.11	-2.71***	-0.09	-1.14	-0.05	-0.66	-0.06	-0.93
Sequencing	-0.19	-4.43***	-0.24	-5.62***	-0.15	-3.30***	-0.01	-0.27	-0.01	-0.17	-0.03	-0.55
Fit	0.17	1.78*	0.15	1.50	0.14	1.39	-0.11	-0.93	-0.14	-1.20	0.16	1.11
Control variables:												
Non-woman-owned	0.10	0.36	0.02	0.08	0.23	1.50	0.36	1.23	0.35	1.24	0.46	2.10*
Non-minority-owned	0.01	0.04	-0.11	-0.48	0.34	2.40**	0.12	0.35	0.05	0.14	0.69	3.12***
Non-HubZone-owned	-0.24	-0.67	-0.39	-1.11	0.10	0.40	-0.10	-0.31	-0.11	-0.31	0.28	0.91
Industry volatility	-0.07	-0.62	0.01	0.07	-0.01	-0.12	-0.04	-0.29	0.05	0.40	-0.03	-0.28
State innovativeness	0.00	0.03	0.01	0.15	0.04	0.91	0.01	0.22	0.03	0.56	0.13	2.15**
Firm age	0.08	1.41	0.04	0.75	-0.09	-1.37	0.52	5.88***	0.50	6.00***	0.16	1.54
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.16		0.18		0.13		0.26		0.27		0.13	
Adjusted R^2	0.09		0.12		0.06		0.20		0.22		0.06	

N= 239

*** p<0.01; ** p<0.05; * p<0.1

Appendix 25: Sensitivity analysis – system of equations (SUR) results – full sample, clusters with no prior awards and with prior awards

	Equation 1 Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)		**Equation 1** Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)		**Equation 1** Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)	
	Full sample				No prior awards				With prior awards			
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level constructs												
Initial commitment	-0.16	-3.01***	-0.24	-4.47***	-0.48	-3.42***	-0.49	-4.59***	0.00	0.02	-0.05	-1.36
Discontinuation	-0.04	-0.31	-0.05	-0.49	-0.25	-1.00	-0.27	-1.38	0.07	0.80	0.04	0.39
Fit	-0.08	-0.73	-0.13	-1.19	0.23	0.97	0.27	1.48	-0.01	-0.08	-0.06	-0.70
Portfolio-level constructs												
Initial commitment									-0.09	-2.05**	-0.13	-2.49**
Sequencing									-0.11	-3.32***	-0.18	-4.44***
Fit	0.25	2.16**	0.32	2.92***					0.13	1.74*	0.17	1.90*
Control variables:												
Non-woman-owned	0.38	1.38	0.48	1.97	0.42	0.79	0.70	1.83*	-0.01	-0.02	0.01	0.03
Non-minority-owned	-0.03	-0.09	-0.14	-0.44	0.02	0.03	-0.16	-0.27	0.05	0.25	-0.01	-0.06
Non-HubZone-owned	-0.38	-1.31	-0.51	-1.96	-0.08	-0.15	-0.24	-0.63	-0.22	-1.22	-0.31	-1.36
Industry volatility	-0.27	-3.47***	-0.17	-2.06	-0.33	-1.75	-0.11	-0.73	-0.09	-0.90	-0.04	-0.49
State innovativeness	-0.03	-0.63	-0.05	-0.91	0.04	0.38	0.01	0.07	0.02	0.56	0.03	0.75
Firm age	0.06	1.13	-0.06	-1.19	0.57	4.15***	0.47	4.33***	0.03	0.65	0.03	0.53
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
N	367		367		128		128		239		239	
R^2	0.24		0.38		0.33		0.39		0.15		0.17	
Adjusted R^2	0.20		0.35		0.24		0.31		0.09		0.11	

*** p<0.01; ** p<0.05; * p<0.1

Appendix 26: Sensitivity analysis of robustness check – system of equations (SUEST) results – full sample, clusters with no prior awards and with prior awards

	Equation 1 Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)		**Equation 1** Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)		**Equation 1** Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)	
	Full sample				No prior awards				With prior awards			
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level constructs												
Initial commitment	-0.16	-2.48**	-0.24	-3.52***	-0.48	-3.53***	-0.49	-4.97***	0.00	0.01	-0.05	-0.86
Discontinuation	-0.04	-0.34	-0.05	-0.53	-0.25	-1.25	-0.27	-1.54	0.07	0.83	0.04	0.40
Fit	-0.08	-0.90	-0.13	-1.36	0.23	1.17	0.27	1.67	-0.01	-0.09	-0.06	-0.74
Portfolio-level constructs												
Initial commitment									-0.09	-2.43**	-0.13	-2.86***
Sequencing									-0.11	-3.79***	-0.18	-4.98***
Fit	0.25	2.48**	0.32	3.17***					0.13	1.80*	0.17	1.98**
Control variables:												
Non-woman-owned	0.38	1.47	0.48	2.15**	0.42	1.25	0.70	2.77***	-0.01	-0.02	0.01	0.03
Non-minority-owned	-0.03	-0.10	-0.14	-0.52	0.02	0.03	-0.16	-0.31	0.05	0.31	-0.01	-0.07
Non-HubZone-owned	-0.38	-1.05	-0.51	-1.45	-0.08	-0.14	-0.24	-0.53	-0.22	-0.67	-0.31	-0.83
Industry volatility	-0.27	-2.61***	-0.17	-1.78*	-0.33	-1.57	-0.11	-0.66	-0.09	-0.80	-0.04	-0.44
State innovativeness	-0.03	-0.55	-0.05	-0.83	0.04	0.32	0.01	0.06	0.02	0.62	0.03	0.83
Firm age	0.06	0.94	-0.06	-1.10	0.57	3.35***	0.47	4.08***	0.03	0.72	0.03	0.60
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
N	367		367		128		128		239		239	
R^2	0.12		0.15		0.33		0.39		0.15		0.17	
Adjusted R^2	0.08		0.11		0.24		0.31		0.09		0.11	

*** p<0.01; ** p<0.05; * p<0.1

Appendix 27: Robustness check – OLS model results – full sample – DV: initial commitment

	(1) Observables		(2) Unobservables		(3) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:								
Role legitimacy								
Manager CEO	-0.05	-0.36					-0.05	-0.39
PI CEO	-0.04	-0.31					-0.02	-0.13
PI's firm tenure	-0.21	-2.53**					-0.23	-2.81***
Manager's technical experience	-0.13	-1.33					-0.11	-1.22
PI's technical experience	0.15	1.96**					0.10	1.36
Manager's entrepreneurial experience	-0.17	-2.08**					-0.14	-1.72
PI's entrepreneurial experience	0.04	0.51					0.05	0.67
Resource legitimacy								
Manager's elite education	0.14	1.61					0.12	1.31
PI's elite education	-0.10	-1.41					-0.07	-0.88
Manager's MBA	-0.17	-0.94					-0.20	-1.19
PI's MBA	0.15	0.75					0.06	0.28
Manager's PhD	0.14	0.82					0.13	0.72
PI's PhD	0.06	0.19					-0.01	-0.04
Manager's professorship	0.10	0.61					0.12	0.70
PI's professorship	0.26	1.44					0.29	1.66
Intellectual legitimacy								
Manager's patents	-0.09	-1.02					-0.10	-1.07
PI's patents	0.16	2.32**					0.15	2.12
Manager's publications	0.01	0.13					0.01	0.08
PI's publications	-0.18	-2.17**					-0.17	-2.01*
Abstract readability	0.25	0.26					0.06	0.06
Capabilities								
R&D capability			0.73	1.29			0.56	0.92
Managerial capability			0.42	1.06			-0.01	-0.02
Intellectual Capability			-0.24	-0.62			-0.19	-0.40
Project appeal								
Project scope (broad)					-0.30	-2.87***	-0.29	-2.41**
Cancer detection and diagnosis research					0.22	1.22	0.24	1.33
Cancer treatment research					0.20	1.07	0.20	1.07
Cancer biology research					0.58	2.54**	0.56	2.39**
Control variables:								
Non-woman-owned	0.06	0.26	0.11	0.54	0.14	0.72	-0.01	-0.03
Non-minority-owned	0.15	0.53	0.14	0.49	0.16	0.56	0.16	0.57
Non-HubZone-owned	-0.13	-0.35	-0.27	-0.75	-0.29	-0.80	-0.12	-0.34
Industry volatility	-0.04	-0.32	0.05	0.53	-0.01	-0.15	-0.09	-0.83
State innovativeness	0.04	0.65	0.02	0.39	0.02	0.38	0.03	0.61
Firm age	0.20	2.68***	0.04	0.76	0.08	1.59	0.23	2.90***
Year dummies	Incl.		Incl.		Incl.		Incl.	
R^2	0.16		0.05		0.08		0.20	
Adjusted R^2	0.08		0.01		0.04		0.10	

N= 367

*** p<0.01; ** p<0.05; * p<0.1

Appendix 28: Robustness check – OLS model results – cluster with no prior awards – DV: initial commitment

	(1) Observables		(2) Unobservables		(3) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:								
Role legitimacy								
Manager CEO	-0.11	-0.57					-0.14	-0.67
PI CEO	0.18	0.86					0.24	1.16
PI's firm tenure	-0.35	-2.02*					-0.34	-2.00*
Manager's technical experience	-0.04	-0.27					-0.02	-0.16
PI's technical experience	0.03	0.26					0.00	0.03
Manager's entrepreneurial experience	-0.15	-1.23					-0.19	-1.41
PI's entrepreneurial experience	0.09	0.65					0.13	0.80
Resource legitimacy								
Manager's elite education	-0.04	-0.31					-0.07	-0.59
PI's elite education	-0.05	-0.52					-0.06	-0.60
Manager's MBA	-0.11	-0.50					-0.09	-0.38
PI's MBA	0.29	0.69					0.16	0.36
Manager's PhD	0.04	0.14					0.03	0.11
PI's PhD	0.27	0.76					0.33	0.79
Manager's professorship	-0.06	-0.25					-0.10	-0.36
PI's professorship	0.47	1.93*					0.51	2.10**
Intellectual legitimacy								
Manager's patents	-0.01	-0.05					0.01	0.04
PI's patents	0.08	0.73					0.09	0.69
Manager's publications	-0.15	-1.15					-0.22	-1.59
PI's publications	-0.13	-1.17					-0.11	-0.78
Abstract readability	0.04	0.03					-0.19	-0.12
Capabilities								
R&D capability			0.81	1.10			0.27	0.30
Managerial capability			-0.26	-0.59			-1.01	-1.78*
Intellectual Capability			-0.57	-0.88			-0.15	-0.16
Project appeal								
Project scope (broad)					-0.19	-1.05	-0.10	-0.46
Cancer detection and diagnosis research					-0.10	-0.29	0.06	0.16
Cancer treatment research					-0.10	-0.27	0.15	0.38
Cancer biology research					0.25	0.53	0.21	0.44
Control variables:								
Non-woman-owned	0.06	0.17	-0.11	-0.34	-0.03	-0.10	0.15	0.42
Non-minority-owned	0.21	0.61	0.30	1.27	0.20	0.76	0.28	0.76
Non-HubZone-owned	0.03	0.07	-0.24	-0.76	-0.22	-0.71	-0.01	-0.03
Industry volatility	-0.08	-0.47	-0.15	-0.96	-0.17	-1.12	-0.06	-0.34
State innovativeness	0.04	0.59	0.00	0.02	0.01	0.15	0.04	0.50
Firm age	0.19	1.60	0.02	0.33	0.03	0.46	0.25	2.03**
Year dummies	Incl.		Incl.		Incl.		Incl.	
R^2	0.30		0.11		0.10		0.34	
Adjusted R^2	0.06		-0.01		-0.03		0.04	

N= 128

*** p<0.01; ** p<0.05; * p<0.1

Appendix 29: Robustness check – OLS model results – cluster with prior awards – DV: initial commitment

	(1) Observables		(2) Unobservables		(3-1) Distortions		(3-2) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:										
Role legitimacy										
Manager CEO	-0.02	-0.10							-0.10	-0.47
PI CEO	-0.17	-0.86							-0.16	-0.80
PI’s firm tenure	-0.16	-1.31							-0.16	-1.21
Manager’s technical experience	-0.12	-0.91							-0.10	-0.78
PI’s technical experience	0.20	1.69							0.16	1.32
Manager’s entrepreneurial experience	-0.21	-1.87*							-0.15	-1.28
PI’s entrepreneurial experience	0.03	0.24							0.05	0.47
Resource legitimacy										
Manager’s elite education	0.18	1.60							0.16	1.38
PI’s elite education	-0.10	-0.93							-0.04	-0.42
Manager’s MBA	-0.17	-0.52							-0.19	-0.57
PI’s MBA	-0.03	-0.11							-0.20	-0.63
Manager’s PhD	0.22	0.80							0.14	0.47
PI’s PhD	-0.16	-0.30							-0.29	-0.52
Manager’s professorship	0.19	0.70							0.15	0.53
PI’s professorship	0.12	0.50							0.16	0.71
Intellectual legitimacy										
Manager’s patents	-0.14	-1.26							-0.19	-1.74*
PI’s patents	0.19	1.98*							0.17	1.90*
Manager’s publications	0.06	0.45							0.11	0.79
PI’s publications	-0.22	-1.89*							-0.23	-2.14**
Abstract readability	0.70	0.56							0.18	0.15
Capabilities										
R&D capability			0.61	0.72					-0.03	-0.03
Managerial capability			0.59	1.14					0.20	0.37
Intellectual capability			-0.19	-0.39					-0.19	-0.31
Project appeal										
Project scope (broad)					-0.34	-2.28**			-0.35	-2.03**
Cancer detection and diagnosis research					0.36	1.56			0.21	0.83
Cancer treatment research					0.38	1.62			0.16	0.65
Cancer biology research					0.63	2.30**			0.67	2.28**
Prior funding decisions										
Initial commitment (portfolio)							0.22	2.16**	0.22	2.15**
Sequencing (portfolio)							-0.02	-0.29	-0.02	-0.24
Fit (portfolio)							0.35	2.01**	0.28	1.50
Control variables:										
Non-woman-owned	0.17	0.57	0.25	0.94	0.21	0.80	0.27	1.09	0.09	0.30
Non-minority-owned	0.17	0.45	0.10	0.26	0.12	0.31	0.01	0.02	0.01	0.04
Non-HubZone-owned	-0.26	-0.37	-0.38	-0.56	-0.51	-0.72	-0.49	-0.69	-0.31	-0.46
Industry volatility	0.03	0.18	0.16	1.33	0.05	0.37	0.12	0.96	-0.11	-0.65
State innovativeness	0.01	0.20	0.00	0.01	0.00	-0.03	-0.01	-0.15	-0.05	-0.66
Firm age	0.09	0.68	-0.09	-0.94	-0.03	-0.39	0.06	0.76	0.15	1.00
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.17		0.07		0.10		0.11		0.27	
Adjusted R^2	0.05		0.01		0.04		0.06		0.11	

N= 239

*** p<0.01; ** p<0.05; * p<0.1

Appendix 30: Robustness check – Logit model results – full sample – DV: discontinuation

	(1) Observables		(2) Unobservables		(3) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:								
Role legitimacy								
Manager CEO	-0.13	-0.38					0.01	0.03
PI CEO	-1.06	-3.17***					-1.01	-2.88***
PI's firm tenure	0.30	1.18					0.37	1.45
Manager's technical experience	0.19	0.75					0.26	0.99
PI's technical experience	-0.22	-0.93					-0.23	-0.93
Manager's entrepreneurial experience	-0.04	-0.17					-0.08	-0.26
PI's entrepreneurial experience	-0.01	-0.02					-0.07	-0.25
Resource legitimacy								
Manager's elite education	0.03	0.17					0.02	0.10
PI's elite education	0.10	0.59					0.17	0.98
Manager's MBA	0.15	0.30					0.12	0.22
PI's MBA	-1.17	-1.35					-1.19	-1.27
Manager's PhD	0.24	0.50					0.36	0.75
PI's PhD	0.07	0.10					-0.32	-0.44
Manager's professorship	-0.05	-0.12					-0.05	-0.12
PI's professorship	-0.57	-1.55					-0.58	-1.46
Intellectual legitimacy								
Manager's patents	0.31	1.53					0.31	1.50
PI's patents	0.19	1.03					0.14	0.79
Manager's publications	-0.25	-1.03					-0.23	-0.88
PI's publications	-0.24	-1.33					-0.28	-1.30
Abstract readability	-0.07	-0.54					-0.09	-0.62
Efficacy								
Project duration	0.33	2.37**					0.37	2.43**
Invention activity	-0.31	-1.91*					-0.65	-3.22***
Capabilities								
R&D capability			-0.05	-0.45			0.00	0.00
Managerial capability			0.16	1.24			0.52	2.72***
Intellectual capability			-0.02	-0.16			0.10	0.43
Project appeal								
Project scope (broad)					0.14	0.55	0.07	0.20
Cancer detection and diagnosis research					0.82	2.23**	0.90	2.01**
Cancer treatment research					0.91	2.41**	0.72	1.58
Cancer biology research					0.92	1.90*	0.98	1.63
Prior funding decisions								
Initial commitment (project)					0.03	0.24	-0.04	-0.27
Control variables:								
Non-woman-owned	-0.24	-0.43	0.14	0.31	0.02	0.05	-0.45	-0.78
Non-minority-owned	-0.20	-0.24	-0.26	-0.39	-0.30	-0.46	-0.32	-0.34
Non-HubZone-owned	0.50	0.73	1.03	1.83*	0.95	1.72*	0.69	0.94
Industry volatility	-0.21	-0.58	-0.25	-0.88	-0.35	-1.14	-0.34	-0.88
State innovativeness	0.24	1.57	0.21	1.73*	0.24	1.98**	0.28	1.71*
Firm age	-0.12	-0.60	-0.04	-0.28	0.03	0.22	-0.21	-0.98
Year dummies	Incl.		Incl.		Incl.		Incl.	
Pseudo R^2	0.19		0.09		0.10		0.22	

N= 360

*** p<0.01; ** p<0.05; * p<0.1

Appendix 31: Robustness check – Logit model results – cluster with no prior awards – DV: discontinuation

	(1) Observables		(2) Unobservables		(3) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:								
Role legitimacy								
Manager CEO	0.42	0.50					1.23	1.03
PI CEO	-1.51	-2.14**					-2.34	-1.83*
PI's firm tenure	0.72	1.30					0.96	0.97
Manager's technical experience	0.41	0.97					0.61	1.22
PI's technical experience	0.03	0.06					-0.37	-0.60
Manager's entrepreneurial experience	-0.14	-0.37					0.01	0.02
PI's entrepreneurial experience	-0.13	-0.28					-0.42	-0.50
Resource legitimacy								
Manager's elite education	-0.04	-0.08					0.04	0.07
PI's elite education	0.10	0.30					0.58	1.75*
Manager's MBA	-0.35	-0.49					-0.82	-0.79
PI's MBA	-1.80	-1.24					-2.42	-1.60
Manager's PhD	-0.50	-0.66					-0.28	-0.21
PI's PhD	-0.02	-0.02					-0.63	-0.50
Manager's professorship	0.37	0.43					0.75	0.63
PI's professorship	-0.81	-0.81					-1.12	-0.68
Intellectual legitimacy								
Manager's patents	0.06	0.12					0.37	0.51
PI's patents	0.27	0.75					0.27	0.65
Manager's publications	-0.03	-0.05					-0.34	-0.40
PI's publications	-0.26	-0.80					0.24	0.43
Abstract readability	0.04	0.12					-0.22	-0.60
Efficacy								
Project duration	0.43	1.47					0.77	2.27**
Invention activity	-0.07	-0.19					-0.28	-0.64
Capabilities								
R&D capability							0.44	1.50
Managerial capability							0.62	1.29
Intellectual capability							-0.90	-1.54
Project appeal								
Project scope (broad)					-0.51	-1.02	-0.91	-1.38
Cancer detection and diagnosis research					1.21	1.76*	1.81	1.61
Cancer treatment research					1.39	2.03**	1.41	1.44
Cancer biology research					2.42	2.41**	4.17	2.75***
Prior funding decisions								
Initial commitment (project)					-0.12	-0.48	-0.17	-0.33
Control variables:								
Non-woman-owned	0.78	0.59	1.52	1.30	1.56	1.31	0.22	0.13
Non-minority-owned	-0.88	-0.60	-1.58	-1.33	-1.69	-1.31	-0.43	-0.22
Non-HubZone-owned	0.15	0.16	0.91	1.17	1.06	1.29	0.08	0.06
Industry volatility	-0.67	-0.86	-0.33	-0.65	-0.49	-0.95	-0.97	-0.98
State innovativeness	0.07	0.24	0.04	0.18	0.16	0.69	0.08	0.24
Firm age	-0.65	-1.53	-0.30	-1.27	-0.17	-0.72	-0.62	-1.00
Year dummies	Incl.		Incl.		Incl.		Incl.	
Pseudo R^2	0.24		0.13		0.15		0.35	

N= 124

*** p<0.01; ** p<0.05; * p<0.1

Appendix 32: Robustness check – Logit model results – cluster with prior awards – DV: discontinuation

	(1) Observables		(2) Unobservables		(3-1) Distortions		(3-2) Distortions		(4) Full Model	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:										
Role legitimacy										
Manager CEO	-0.47	-0.97							-0.49	-0.91
PI CEO	-1.14	-2.33**							-1.01	-1.96*
PI's firm tenure	0.15	0.39							0.46	1.10
Manager's technical experience	0.17	0.49							0.25	0.61
PI's technical experience	-0.44	-1.46							-0.47	-1.26
Manager's entrepreneurial experience	0.01	0.03							0.02	0.04
PI's entrepreneurial experience	0.20	0.60							0.06	0.15
Resource legitimacy										
Manager's elite education	0.07	0.26							0.06	0.20
PI's elite education	0.09	0.43							0.17	0.71
Manager's MBA	0.53	0.60							0.54	0.56
PI's MBA	-0.74	-0.78							-1.05	-0.94
Manager's PhD	0.39	0.56							0.71	1.02
PI's PhD	0.18	0.15							-0.31	-0.26
Manager's professorship	-0.02	-0.05							-0.11	-0.21
PI's professorship	-0.76	-1.50							-0.96	-1.66
Intellectual legitimacy										
Manager's patents	0.55	2.03**							0.66	2.07**
PI's patents	0.18	0.76							0.08	0.31
Manager's publications	-0.33	-0.83							-0.36	-0.76
PI's publications	-0.36	-1.41							-0.43	-1.66
Abstract readability	-0.17	-0.88							-0.13	-0.65
Efficacy										
Project duration	0.22	1.17							0.32	1.58
Invention activity	-0.41	-1.78*							-0.78	-2.65**
Capabilities										
R&D capability									-0.28	-1.20
Managerial capability									0.61	2.01**
Intellectual capability									0.32	1.04
Project appeal										
Project scope (broad)					0.32	1.03			0.27	0.58
Cancer detection and diagnosis research					0.66	1.38			0.43	0.67
Cancer treatment research					0.72	1.47			0.42	0.62
Cancer biology research					0.38	0.64			-0.22	-0.25
Prior funding decisions										
Initial commitment (project)							0.04	0.29	0.04	0.22
Initial commitment (portfolio)							0.01	0.05	-0.11	-0.53
Sequencing (portfolio)							-0.32	-2.07**	-0.24	-1.35
Fit (portfolio)							-0.01	-0.04	0.28	0.67
Control variables:										
Non-woman-owned	-0.57	-0.76	-0.04	-0.07	-0.23	-0.42	-0.17	-0.33	-0.35	-0.40
Non-minority-owned	-0.13	-0.09	0.17	0.19	0.11	0.13	0.43	0.52	-0.33	-0.21
Non-HubZone-owned	0.19	0.15	0.85	0.95	0.78	0.89	0.88	0.99	0.41	0.32
Industry volatility	0.01	0.01	-0.27	-0.74	-0.34	-0.87	-0.31	-0.84	-0.09	-0.17
State innovativeness	0.40	1.99**	0.27	1.68**	0.32	2.05**	0.33	2.13**	0.53	2.17**
Firm age	-0.01	-0.02	0.01	0.07	0.09	0.48	0.15	0.77	-0.26	-0.77
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.	
Pseudo R^2	0.24		0.11		0.11		0.12		0.30	

N= 236

*** p<0.01; ** p<0.05; * p<0.1

Appendix 33: Robustness check – system of equations (SUEST) results – full sample

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level funding												
Initial commitment	-0.17	-2.69***	-0.22	-3.64***	-0.03	-0.49	0.03	0.55	0.02	0.36	0.03	0.59
Discontinuation	0.00	0.02	0.00	-0.01	-0.17	-1.58	0.10	0.96	0.05	0.49	-0.26	-2.56**
Fit	-0.10	-1.02	-0.13	-1.37	-0.05	-0.57	-0.04	-0.44	-0.08	-0.90	-0.05	-0.55
Portfolio-level funding												
Fit	0.22	2.06**	0.26	2.57**	0.08	0.88	-0.05	-0.50	-0.03	-0.27	0.07	0.67
Role legitimacy												
Manager CEO	-0.13	-0.83	-0.18	-1.09	-0.05	-0.38	-0.33	-2.34**	-0.35	-2.45**	-0.10	-0.77
PI CEO	0.05	0.38	0.05	0.37	-0.15	-1.14	0.08	0.79	0.06	0.59	-0.11	-1.01
PI’s firm tenure	-0.35	-3.25***	-0.34	-3.71***	-0.08	-0.94	-0.19	-1.96*	-0.19	-2.34**	0.02	0.19
Manager’s technical experience	0.06	0.47	0.08	0.56	0.10	1.04	-0.03	-0.40	-0.05	-0.66	0.13	1.20
PI’s technical experience	0.06	0.64	0.09	1.13	0.00	-0.03	-0.02	-0.33	-0.04	-0.62	-0.07	-0.96
Manager’s entrepreneurial experience	-0.02	-0.15	-0.05	-0.36	-0.03	-0.29	0.03	0.27	0.02	0.20	0.04	0.42
PI’s entrepreneurial experience	0.12	1.31	0.06	0.78	0.01	0.15	-0.11	-1.36	-0.09	-1.13	-0.11	-1.31
Resource legitimacy												
Manager’s elite education	-0.07	-0.95	-0.04	-0.49	-0.02	-0.35	0.10	1.40	0.10	1.36	0.11	1.79*
PI’s elite education	0.05	0.71	0.08	1.11	0.05	0.80	-0.03	-0.45	0.02	0.35	0.00	0.07
Manager’s MBA	0.42	1.78*	0.41	2.08**	0.16	0.66	-0.04	-0.27	0.03	0.24	-0.24	-1.24
PI’s MBA	-0.29	-1.27	-0.33	-1.33	0.04	0.13	-0.23	-1.37	-0.23	-1.32	0.19	0.87
Manager’s PhD	0.02	0.11	0.10	0.44	0.11	0.59	0.06	0.38	0.10	0.56	-0.11	-0.71
PI’s PhD	-0.23	-0.61	-0.12	-0.45	-0.06	-0.23	-0.41	-1.01	-0.34	-1.03	-0.01	-0.05
Manager’s professorship	-0.11	-0.67	-0.13	-0.76	0.03	0.16	-0.10	-0.78	-0.01	-0.08	0.02	0.14
PI’s professorship	-0.09	-0.69	-0.05	-0.36	-0.41	-2.75***	0.17	1.25	0.14	1.00	-0.33	-2.76***
Intellectual legitimacy												
Manager’s patents	-0.06	-0.76	-0.06	-0.78	0.02	0.22	-0.12	-1.91*	-0.07	-0.96	-0.01	-0.09
PI’s patents	-0.06	-0.81	-0.04	-0.65	0.08	1.06	-0.05	-0.87	0.00	0.00	0.13	2.11**
Manager’s publications	0.03	0.25	-0.01	-0.06	-0.13	-1.15	0.07	0.78	0.02	0.24	-0.04	-0.32
PI’s publications	0.03	0.31	0.01	0.08	0.15	1.61	0.06	0.90	0.08	1.16	0.17	2.16**
Abstract readability	0.02	0.41	-0.01	-0.16	-0.01	-0.19	0.02	0.54	0.00	0.06	0.00	-0.06
Efficacy												
Project duration	-0.14	-2.41**	-0.18	-3.09***	-0.12	-2.27**	-0.04	-0.96	-0.08	-1.79*	0.02	0.39
Invention activity	0.13	1.63	0.05	0.68			0.31	3.96***	0.26	3.41***		
Capabilities												
R&D capability	-0.01	-0.14	0.01	0.07	0.03	0.44	-0.02	-0.42	0.00	-0.02	0.12	2.03**
Managerial capability	0.09	0.73	0.05	0.47	0.20	2.12**	-0.09	-0.92	-0.04	-0.43	0.22	2.08*
Intellectual capability	-0.09	-1.33	-0.02	-0.37	0.08	1.19	-0.02	-0.47	-0.01	-0.29	0.08	1.47
R&DCapXManCap	0.00	-0.06	0.00	0.03	-0.02	-0.45	0.05	0.99	0.02	0.35	-0.01	-0.23
R&DCapXIntCap	0.01	0.06	-0.01	-0.15	0.06	0.73	0.02	0.31	-0.01	-0.14	0.03	0.52
IntCapXManCap	0.00	0.02	0.07	0.83	0.01	0.08	0.08	1.17	0.08	1.26	0.14	1.58
Control variables:												
Non-woman-owned	0.48	1.55	0.50	2.06**	0.03	0.16	0.27	1.02	0.34	1.36	-0.08	-0.48
Non-minority-owned	-0.40	-0.96	-0.51	-1.54	0.16	0.86	-0.43	-1.37	-0.43	-1.28	0.30	1.85
Non-HubZone-owned	-0.24	-0.66	-0.26	-0.80	-0.16	-0.60	-0.05	-0.17	-0.03	-0.10	-0.03	-0.17
Industry volatility	-0.22	-2.50**	-0.16	-2.04**	-0.05	-0.69	-0.06	-0.86	0.02	0.24	-0.04	-0.60
State innovativeness	-0.09	-1.46	-0.09	-1.64	0.01	0.16	-0.03	-0.65	-0.03	-0.59	0.07	1.38
Firm age	0.14	1.37	0.04	0.47	-0.20	-2.57**	0.51	5.81***	0.53	7.10***	-0.02	-0.34
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.27		0.31		0.24		0.49		0.50		0.38	
Adjusted R^2	0.17		0.22		0.14		0.42		0.43		0.30	

N= 367; *** $p<0.01$; ** $p<0.05$; * $p<0.1$

Appendix 34: Robustness check – system of equations (SUEST) results – cluster with no prior awards

	Equation 1 Sales Yield		**Equation 2** Employment Yield		**Equation 3** Innovation Yield		**Equation 4** Sales Performance		**Equation 5** Employment Performance		**Equation 6** Innovation Performance	
	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value	Coefficient estimate	t-value
Independent variables:												
Project-level funding												
Initial commitment	-0.32	-2.63**	-0.34	-4.01***	0.13	0.73	-0.10	-1.25	-0.14	-1.73	0.13	1.13
Discontinuation	-0.10	-0.49	-0.11	-0.78	-0.19	-0.75	-0.05	-0.36	-0.14	-1.09	-0.09	-0.57
Fit	-0.04	-0.26	0.03	0.25	-0.18	-0.76	-0.03	-0.28	0.01	0.06	-0.12	-0.82
Role legitimacy												
Manager CEO	-0.06	-0.27	0.02	0.10	0.22	0.80	-0.06	-0.42	-0.01	-0.03	0.09	0.46
PI CEO	-0.07	-0.29	-0.15	-0.93	-0.82	-2.52**	0.04	0.29	-0.15	-1.05	-0.44	-2.19**
PI's firm tenure	-0.40	-1.58	-0.29	-1.79*	-0.34	-1.10	-0.31	-1.83*	-0.33	-2.05*	-0.26	-1.43
Manager's technical experience	-0.06	-0.33	-0.04	-0.36	0.29	1.49	-0.08	-0.66	-0.10	-0.91	0.12	0.98
PI's technical experience	-0.15	-0.84	-0.01	-0.12	-0.08	-0.41	-0.10	-1.27	-0.06	-0.69	-0.04	-0.36
Manager's entrepreneurial experience	0.35	1.62	0.17	1.12	0.05	0.18	0.23	1.65	0.16	1.07	0.05	0.32
PI's entrepreneurial experience	0.08	0.44	0.01	0.08	0.03	0.19	0.11	0.81	0.12	1.00	0.06	0.53
Resource legitimacy												
Manager's elite education	0.13	1.24	0.12	1.39	0.00	0.00	0.07	0.89	0.11	1.07	-0.05	-0.46
PI's elite education	0.05	0.58	0.11	1.57	-0.06	-0.39	0.04	0.51	0.10	1.19	-0.04	-0.45
Manager's MBA	0.50	1.84*	0.29	1.49	0.24	0.73	0.28	1.76*	0.18	0.89	0.12	0.61
PI's MBA	0.42	1.14	0.56	2.01*	0.26	0.37	0.04	0.19	0.31	1.16	-0.02	-0.05
Manager's PhD	-0.35	-1.30	-0.30	-1.21	0.01	0.02	-0.20	-1.17	-0.34	-1.47	-0.01	-0.05
PI's PhD	-0.07	-0.13	0.18	0.64	-0.13	-0.26	-0.03	-0.09	0.17	0.73	-0.12	-0.40
Manager's professorship	0.29	1.12	0.17	0.90	0.45	1.22	0.15	0.86	0.14	0.68	0.24	1.04
PI's professorship	0.22	0.86	0.24	1.15	-0.70	-1.94*	0.10	0.68	0.13	0.77	-0.45	-2.16**
Intellectual legitimacy												
Manager's patents	-0.02	-0.08	0.02	0.11	-0.01	-0.03	-0.05	-0.39	-0.02	-0.13	-0.03	-0.22
PI's patents	0.14	0.84	0.13	1.23	0.48	2.92***	0.09	0.85	0.15	1.58	0.29	2.78***
Manager's publications	0.30	1.15	0.23	1.20	-0.15	-0.71	0.22	1.51	0.27	1.52	-0.02	-0.17
PI's publications	0.11	0.66	0.04	0.32	0.16	0.73	0.05	0.70	0.04	0.48	0.06	0.48
Abstract readability	0.10	1.13	0.04	0.51	-0.13	-0.98	0.10	1.59	0.09	1.43	-0.08	-1.00
Efficacy												
Project duration	-0.17	-1.31	-0.17	-2.46**	-0.46	-3.34***	-0.01	-0.18	-0.07	-1.03	-0.27	-2.93***
Invention activity	0.09	0.59	0.01	0.05			0.03	0.29	0.04	0.39		
Capabilities												
R&D capability	0.10	0.65	0.09	0.84	0.34	1.96*	0.01	0.08	0.03	0.32	0.19	1.84*
Managerial capability	0.80	2.55**	0.53	3.27***	0.34	0.73	0.53	2.76**	0.57	3.49***	0.14	0.53
Intellectual capability	-0.37	-1.92*	-0.15	-1.19	-0.01	-0.06	-0.23	-2.12**	-0.15	-1.38	-0.02	-0.16
R&DCapXManCap	-0.25	-1.67	-0.22	-2.41**	0.35	1.95*	-0.15	-1.49	-0.25	-2.55**	0.26	2.65***
R&DCapXIntCap	-0.20	-1.82*	-0.17	-2.32**	-0.15	-1.33	-0.06	-1.00	-0.11	-1.61	-0.05	-0.78
IntCapXManCap	-0.35	-1.21	-0.04	-0.31	-0.66	-2.00*	-0.24	-1.28	-0.04	-0.29	-0.37	-1.87*
Control variables:												
Non-woman-owned	0.45	1.25	0.67	2.21**	-0.41	-0.77	0.13	0.44	0.55	2.73***	-0.30	-0.97
Non-minority-owned	-0.43	-0.54	-0.47	-1.01	0.76	1.23	-0.14	-0.35	-0.26	-0.62	0.58	1.60
Non-HubZone-owned	0.00	-0.01	-0.11	-0.35	-0.37	-0.75	-0.01	-0.02	-0.15	-0.51	-0.12	-0.41
Industry volatility	-0.10	-0.56	-0.06	-0.47	-0.07	-0.34	-0.03	-0.27	0.00	0.01	0.00	0.04
State innovativeness	-0.02	-0.22	-0.02	-0.30	0.14	1.08	-0.01	-0.15	-0.04	-0.42	0.10	1.27
Firm age	0.46	2.49**	0.35	2.88**	-0.03	-0.14	0.30	2.49**	0.34	2.77**	0.02	0.22
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.63		0.68		0.44		0.56		0.64		0.45	
Adjusted R^2	0.44		0.52		0.16		0.34		0.46		0.17	

N= 128; *** p<0.01; ** p<0.05; * p<0.1

Appendix 35: Robustness check – system of equations (SUEST) results – cluster with prior awards

	Equation 1 Sales Yield		Equation 2 Employment Yield		Equation 3 Innovation Yield		Equation 4 Sales Performance		Equation 5 Employment Performance		Equation 6 Innovation Performance	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Independent variables:												
Project-level funding												
Initial commitment	-0.05	-0.83	-0.09	-1.67	-0.03	-0.62	0.08	1.14	0.07	1.28	0.00	0.02
Discontinuation	0.14	1.30	0.09	0.87	0.01	0.12	0.19	1.60	0.11	0.90	-0.18	-1.52
Fit	-0.02	-0.18	-0.07	-0.77	-0.06	-0.75	-0.12	-1.07	-0.19	-1.82*	-0.09	-0.76
Portfolio-level funding												
Initial commitment	-0.11	-1.95*	-0.13	-2.13**	-0.10	-2.15**	-0.04	-0.45	-0.01	-0.14	-0.03	-0.54
Sequencing	-0.19	-4.02***	-0.25	-5.08***	-0.14	-3.24***	-0.04	-0.71	-0.04	-0.69	-0.01	-0.27
Fit	0.14	1.52	0.13	1.22	0.12	1.34	-0.16	-1.45	-0.18	-1.50	0.13	1.03
Role legitimacy												
Manager CEO	-0.15	-0.98	-0.27	-1.66	-0.07	-0.54	-0.47	-2.48**	-0.54	-2.94***	-0.03	-0.18
PI CEO	0.08	0.68	0.10	0.86	0.12	1.08	0.13	0.68	0.13	0.75	0.17	1.11
PI's firm tenure	-0.22	-3.63***	-0.27	-3.82***	-0.04	-0.57	-0.16	-1.65	-0.15	-1.83	0.09	0.83
Manager's technical experience	-0.03	-0.35	-0.02	-0.17	0.03	0.43	-0.08	-0.81	-0.10	-1.17	0.23	1.45
PI's technical experience	0.06	0.89	0.05	0.75	0.01	0.07	0.04	0.41	-0.02	-0.18	-0.10	-0.93
Manager's entrepreneurial experience	-0.12	-0.97	-0.10	-0.76	-0.01	-0.15	-0.02	-0.17	-0.01	-0.08	0.02	0.20
PI's entrepreneurial experience	0.05	0.80	0.04	0.60	0.00	0.04	-0.26	-2.83***	-0.22	-2.53**	-0.19	-1.62
Resource legitimacy												
Manager's elite education	0.04	0.56	0.08	0.90	0.05	0.73	0.12	1.17	0.12	1.37	0.15	1.57
PI's elite education	-0.06	-0.87	-0.04	-0.61	0.03	0.60	-0.11	-1.08	-0.06	-0.71	0.00	0.00
Manager's MBA	0.10	0.46	0.10	0.45	-0.12	-0.58	-0.27	-1.16	-0.17	-0.72	-0.57	-2.15**
PI's MBA	-0.34	-1.62	-0.46	-2.02**	-0.16	-0.82	-0.23	-0.91	-0.29	-1.18	0.06	0.18
Manager's PhD	0.03	0.19	0.17	0.87	-0.04	-0.23	0.04	0.19	0.14	0.67	-0.30	-1.19
PI's PhD	-0.48	-1.22	-0.42	-1.44	0.10	0.46	-0.61	-1.04	-0.59	-1.18	0.17	0.44
Manager's professorship	0.01	0.08	0.03	0.22	-0.15	-1.16	-0.07	-0.34	0.08	0.46	-0.25	-1.63
PI's professorship	0.00	0.03	0.02	0.15	-0.12	-1.08	0.22	1.23	0.18	1.00	-0.18	-1.17
Intellectual legitimacy												
Manager's patents	0.01	0.14	0.03	0.35	0.05	0.77	-0.09	-1.15	-0.01	-0.15	-0.02	-0.20
PI's patents	-0.05	-0.83	-0.05	-0.79	-0.02	-0.30	-0.07	-0.88	-0.04	-0.51	0.07	0.88
Manager's publications	-0.04	-0.46	-0.11	-1.31	-0.03	-0.32	0.04	0.35	-0.05	-0.54	-0.01	-0.07
PI's publications	0.03	0.42	0.04	0.50	0.15	2.35**	0.09	1.04	0.11	1.43	0.21	2.31**
Abstract readability	0.00	0.01	-0.03	-0.49	0.00	0.08	-0.02	-0.35	-0.05	-1.03	0.02	0.40
Efficacy												
Project duration	-0.08	-1.49	-0.14	-2.61**	-0.01	-0.17	-0.05	-0.88	-0.08	-1.44	0.09	1.36
Invention activity	0.18	2.12**	0.15	1.82*			0.38	3.87***	0.34	3.58***		
Capabilities												
R&D capability	0.00	0.06	-0.01	-0.11	0.03	0.37	-0.06	-0.74	-0.08	-0.95	0.19	2.21**
Managerial capability	-0.11	-1.22	-0.13	-1.52	0.09	0.91	-0.28	-2.69**	-0.24	-2.58**	0.17	1.13
Intellectual capability	-0.02	-0.40	0.01	0.13	0.05	1.07	-0.01	-0.12	-0.01	-0.16	0.08	1.32
R&DCapXManCap	0.07	1.33	0.07	1.28	-0.02	-0.48	0.16	2.63***	0.14	2.43**	-0.02	-0.32
R&DCapXIntCap	0.04	0.60	0.02	0.30	0.11	1.63	0.07	0.78	0.06	0.63	0.06	0.68
IntCapXManCap	0.07	0.82	0.09	1.16	0.15	1.85*	0.13	1.76*	0.09	1.30	0.24	2.26**
Control variables:												
Non-woman-owned	0.17	0.50	0.10	0.39	0.10	0.58	0.37	1.21	0.30	1.01	0.08	0.39
Non-minority-owned	-0.28	-1.11	-0.44	-1.59	0.23	1.36	-0.54	-1.65	-0.59	-1.58	0.50	2.18**
Non-HubZone-owned	-0.10	-0.29	-0.14	-0.43	0.09	0.37	-0.08	-0.24	-0.01	-0.03	-0.03	-0.10
Industry volatility	-0.12	-1.10	-0.05	-0.55	-0.08	-1.12	-0.12	-0.83	0.00	-0.03	-0.12	-1.32
State innovativeness	-0.03	-0.73	-0.03	-0.67	-0.02	-0.42	-0.06	-1.04	-0.04	-0.67	0.02	0.37
Firm age	0.22	2.10*	0.21	2.59**	-0.17	-1.88*	0.62	4.71***	0.59	5.35***	-0.09	-0.70
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.40		0.43		0.37		0.59		0.59		0.50	
Adjusted R^2	0.25		0.30		0.23		0.50		0.49		0.39	

N= 239; *** p<0.01; ** p<0.05; * p<0.1

Appendix 36: Sensitivity analysis – system of equations (SUR) results – full sample, clusters with no prior awards and with prior awards

	Equation 1 Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)		**Equation 1** Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)		**Equation 1** Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)	
	Full sample				No prior awards				With prior awards			
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Independent variables:												
Project-level Funding												
Initial commitment	-0.14	-2.46**	-0.22	-4.05***	-0.34	-2.17**	-0.41	-3.65***	-0.02	-0.39	-0.07	-1.56
Discontinuation	0.02	0.14	0.01	0.08	0.05	0.20	-0.05	-0.28	0.09	1.10	0.07	0.72
Fit	-0.05	-0.47	-0.13	-1.23	-0.06	-0.28	0.01	0.09	0.00	-0.04	-0.07	-0.90
Portfolio-level Funding												
Initial commitment									-0.09	-1.92*	-0.13	-2.51**
Sequencing									-0.11	-2.95***	-0.19	-4.37***
Fit	0.19	1.63	0.26	2.42**					0.12	1.65	0.14	1.58
Role legitimacy												
Manager CEO	-0.10	-0.57	-0.13	-0.75	-0.21	-0.74	-0.05	-0.27	-0.11	-1.04	-0.17	-1.26
PI CEO	0.07	0.45	0.05	0.42	0.13	0.50	-0.11	-0.59	0.06	0.60	0.10	0.94
PI's firm tenure	-0.32	-3.51***	-0.33	-3.97***	-0.53	-1.85*	-0.38	-1.89*	-0.13	-2.43**	-0.20	-3.21***
Manager's technical experience	0.07	0.49	0.08	0.59	-0.03	-0.16	-0.06	-0.41	-0.02	-0.26	-0.01	-0.07
PI's technical experience	0.04	0.40	0.08	1.00	-0.18	-0.82	-0.04	-0.31	0.02	0.33	0.03	0.52
Manager's entrepreneurial experience	0.04	0.41	-0.04	-0.31	0.42	1.97*	0.23	1.24	-0.07	-0.83	-0.10	-0.94
PI's entrepreneurial experience	0.11	1.32	0.09	1.08	0.04	0.20	0.04	0.22	0.04	0.73	0.04	0.63
Resource legitimacy												
Manager's elite education	-0.11	-1.49	-0.07	-0.95	0.14	0.97	0.17	1.55	0.03	0.53	0.07	1.00
PI's elite education	0.05	0.70	0.08	1.11	-0.01	-0.09	0.10	1.03	-0.05	-0.86	-0.04	-0.77
Manager's MBA	0.45	2.31**	0.44	2.21**	0.69	2.05*	0.37	1.47	0.11	0.74	0.12	0.68
PI's MBA	-0.26	-1.05	-0.25	-1.03	0.39	0.77	0.70	1.94*	-0.21	-1.32	-0.32	-1.70*
Manager's PhD	0.03	0.15	0.11	0.46	-0.36	-1.04	-0.40	-1.37	0.03	0.23	0.20	1.29
PI's PhD	-0.15	-0.44	-0.15	-0.55	0.03	0.05	0.14	0.47	-0.38	-1.14	-0.43	-1.59
Manager's professorship	-0.07	-0.48	-0.08	-0.46	0.27	0.80	0.26	1.04	0.02	0.20	0.05	0.42
PI's professorship	-0.09	-0.69	-0.06	-0.40	0.15	0.47	0.28	1.12	0.00	0.02	0.03	0.22
Intellectual legitimacy												
Manager's patents	-0.08	-1.08	-0.04	-0.52	-0.14	-0.59	0.02	0.09	0.01	0.26	0.05	0.78
PI's patents	-0.05	-0.69	-0.04	-0.65	0.13	0.64	0.16	1.36	-0.01	-0.25	-0.03	-0.52
Manager's publications	0.05	0.43	0.00	-0.02	0.40	1.49	0.31	1.33	-0.03	-0.48	-0.12	-1.83*
PI's publications	0.03	0.42	0.01	0.11	0.14	0.76	0.06	0.44	0.02	0.41	0.03	0.45
Abstract readability	0.04	0.76	0.01	0.18	0.17	1.45	0.07	0.79	0.01	0.24	-0.01	-0.25
Efficacy												
Project duration	-0.10	-1.62	-0.16	-2.56**	-0.13	-0.83	-0.18	-1.97*	-0.04	-0.94	-0.10	-2.03*
Invention activity	0.09	1.10	0.09	1.21	-0.08	-0.40	0.00	-0.03	0.07	1.17	0.09	1.38
Capabilities												
R&D capability	-0.06	-0.74	0.00	-0.05	-0.06	-0.38	0.07	0.51	0.02	0.31	0.04	0.51
Managerial capability	0.17	1.56	0.09	0.89	1.30	3.17**	0.77	3.93***	-0.03	-0.38	-0.07	-0.96
Intellectual capability	-0.13	-1.96*	-0.05	-0.73	-0.51	-2.20*	-0.20	-1.24	-0.02	-0.61	0.01	0.16
R&DCapXManCap	-0.02	-0.28	-0.02	-0.27	-0.42	-2.57**	-0.33	-2.92***	0.05	1.26	0.05	1.10
R&DCapXIntCap	0.02	0.24	-0.01	-0.14	-0.18	-1.37	-0.22	-2.24**	0.03	0.54	0.02	0.35
IntCapXManCap	-0.08	-0.70	0.04	0.48	-0.64	-1.83	-0.06	-0.41	0.01	0.23	0.06	1.08
Control variables:												
Non-woman-owned	0.40	1.32	0.49	1.89	0.33	0.72	0.66	1.94	0.02	0.06	0.02	0.10
Non-minority-owned	-0.29	-0.69	-0.39	-1.09	-0.59	-0.65	-0.48	-0.80	-0.12	-0.53	-0.22	-0.89
Non-HubZone-owned	-0.23	-0.58	-0.31	-1.04	0.13	0.21	-0.09	-0.26	-0.12	-0.62	-0.14	-0.60
Industry volatility	-0.26	-3.21***	-0.20	-2.51**	-0.21	-0.90	-0.11	-0.64	-0.12	-1.17	-0.07	-0.97
State innovativeness	-0.06	-1.15	-0.08	-1.44	0.03	0.28	-0.04	-0.37	0.01	0.18	0.02	0.42
Firm age	0.16	1.69	0.06	0.69	0.54	2.41**	0.44	2.87**	0.12	1.37	0.16	2.11**
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2 (Adjusted R^2)	0.24 (0.14)		0.29 (0.19)		0.60 (0.39)		0.68 (0.52)		0.35 (0.20)		0.40 (0.26)	

*** p<0.01; ** p<0.05; * p<0.1

Appendix 37: Sensitivity analysis of robustness check – system of equations (SUEST) results – full sample, clusters with no prior awards and with prior awards

	Equation 1 Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)		**Equation 1** Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)		**Equation 1** Sales Yield (10% growth)		**Equation 2** Employment Yield (10% growth)	
	Full sample				No prior awards				With prior awards			
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Independent variables:												
Project-level Funding												
Initial commitment	-0.14	-2.28**	-0.21	-3.46***	-0.35	-2.35**	-0.41	-3.86***	-0.02	-0.32	-0.07	-1.25
Discontinuation	0.01	0.11	0.00	-0.02	0.04	0.19	-0.05	-0.32	0.10	1.31	0.08	0.85
Fit	-0.05	-0.61	-0.14	-1.47	-0.03	-0.15	0.02	0.14	0.00	-0.01	-0.07	-0.94
Portfolio-level Funding												
Initial commitment									-0.08	-2.05**	-0.12	-2.61**
Sequencing									-0.11	-3.30***	-0.19	-4.67***
Fit	0.19	1.87*	0.27	2.61***					0.12	1.71*	0.14	1.54
Role legitimacy												
Manager CEO	-0.11	-0.59	-0.14	-0.80	-0.18	-0.63	-0.05	-0.22	-0.11	-0.97	-0.17	-1.22
PI CEO	0.07	0.49	0.05	0.43	0.16	0.57	-0.10	-0.53	0.06	0.55	0.09	0.97
PI's firm tenure	-0.32	-2.51**	-0.33	-3.11***	-0.51	-1.55	-0.38	-1.77*	-0.14	-3.02***	-0.20	-3.67***
Manager's technical experience	0.07	0.47	0.08	0.58	-0.03	-0.16	-0.06	-0.40	-0.03	-0.32	-0.01	-0.11
PI's technical experience	0.04	0.37	0.08	0.94	-0.18	-0.80	-0.04	-0.29	0.02	0.48	0.03	0.60
Manager's entrepreneurial experience	0.04	0.35	-0.03	-0.27	0.42	1.70*	0.22	1.18	-0.07	-0.86	-0.10	-0.94
PI's entrepreneurial experience	0.11	1.02	0.08	0.96	0.02	0.09	0.03	0.20	0.05	0.90	0.04	0.80
Resource legitimacy												
Manager's elite education	-0.10	-1.33	-0.06	-0.86	0.13	0.94	0.17	1.58	0.02	0.46	0.07	0.97
PI's elite education	0.05	0.68	0.08	1.14	-0.01	-0.12	0.10	1.11	-0.05	-0.88	-0.05	-0.79
Manager's MBA	0.45	1.92*	0.44	2.11**	0.66	1.97*	0.36	1.45	0.12	0.78	0.12	0.71
PI's MBA	-0.26	-1.20	-0.25	-1.01	0.41	0.86	0.70	2.04**	-0.21	-1.62	-0.32	-1.87*
Manager's PhD	0.03	0.13	0.10	0.42	-0.35	-1.00	-0.40	-1.29	0.04	0.23	0.20	1.25
PI's PhD	-0.15	-0.42	-0.14	-0.49	0.02	0.03	0.14	0.43	-0.39	-1.06	-0.44	-1.49
Manager's professorship	-0.07	-0.53	-0.08	-0.49	0.26	0.86	0.26	1.07	0.03	0.28	0.06	0.44
PI's professorship	-0.09	-0.75	-0.07	-0.47	0.18	0.61	0.28	1.15	0.01	0.10	0.04	0.25
Intellectual legitimacy												
Manager's patents	-0.08	-1.05	-0.04	-0.44	-0.17	-0.69	0.01	0.06	0.01	0.21	0.05	0.75
PI's patents	-0.05	-0.55	-0.03	-0.50	0.11	0.51	0.16	1.22	-0.02	-0.39	-0.03	-0.57
Manager's publications	0.05	0.40	0.00	-0.01	0.41	1.51	0.31	1.33	-0.03	-0.41	-0.12	-1.60
PI's publications	0.03	0.38	0.01	0.15	0.13	0.71	0.06	0.42	0.02	0.35	0.02	0.40
Abstract readability	0.04	0.84	0.01	0.16	0.18	1.68	0.07	0.85	0.01	0.27	-0.01	-0.22
Efficacy												
Project duration	-0.10	-1.75*	-0.16	-2.64**	-0.12	-0.76	-0.18	-2.09**	-0.04	-0.97	-0.10	-2.11**
Invention activity	0.08	0.89	0.04	0.48	0.05	0.24	0.02	0.16	0.10	1.57	0.11	1.49
Capabilities												
R&D capability	-0.06	-0.59	0.01	0.09	-0.09	-0.46	0.06	0.43	0.01	0.11	0.03	0.44
Managerial capability	0.18	1.35	0.12	1.01	1.22	2.69**	0.76	3.49***	-0.04	-0.56	-0.08	-1.03
Intellectual capability	-0.13	-1.84*	-0.04	-0.72	-0.50	-2.11*	-0.20	-1.23	-0.03	-0.65	0.01	0.13
R&DCapXManCap	-0.02	-0.27	-0.02	-0.26	-0.43	-2.25**	-0.33	-2.73***	0.05	1.43	0.05	1.12
R&DCapXIntCap	0.02	0.20	-0.01	-0.15	-0.18	-1.41	-0.21	-2.30**	0.04	0.88	0.03	0.49
IntCapXManCap	-0.07	-0.63	0.04	0.44	-0.61	-1.60	-0.06	-0.37	0.01	0.11	0.06	0.80
Control variables:												
Non-woman-owned	0.40	1.39	0.48	1.93*	0.39	1.14	0.67	2.18**	0.02	0.08	0.03	0.11
Non-minority-owned	-0.28	-0.76	-0.38	-1.14	-0.65	-0.77	-0.49	-0.87	-0.13	-0.70	-0.23	-1.03
Non-HubZone-owned	-0.22	-0.51	-0.29	-0.76	0.10	0.15	-0.09	-0.25	-0.14	-0.45	-0.15	-0.45
Industry volatility	-0.26	-2.61**	-0.20	-2.26**	-0.20	-0.80	-0.10	-0.59	-0.11	-1.03	-0.07	-0.86
State innovativeness	-0.06	-0.99	-0.08	-1.24	0.03	0.23	-0.04	-0.36	0.00	0.12	0.02	0.40
Firm age	0.16	1.35	0.06	0.62	0.53	2.27**	0.44	2.76**	0.12	1.38	0.16	2.25**
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.		Incl.	
R^2 (Adjusted R^2)	0.24 (0.14)		0.29 (0.19)		0.60 (0.39)		0.68 (0.52)		0.35 (0.20)		0.40 (0.26)	

*** p<0.01; ** p<0.05; * p<0.1

Paper 1

Decomposing the Role of Individual- and Firm-level Capabilities for Scientifically-based Innovation Commercialisation[44]

ABSTRACT

We build on the contingency theory of the resource-based view to decompose the effects of distinct capabilities of science-based ventures on innovation performance and sales performance. Our contribution focuses on the mediation and moderation analysis examining the competing explanations underlying this nomological network of relationships. We examine multi-source, secondary, longitudinal data on 367 projects from 275 small U.S. government-funded research-intensive ventures and find that the effect of research and development, managerial and intellectual capabilities on sales performance is mediated by innovation performance. In addition, our results show that innovation performance has a moderating role, enhancing the effect of managerial capability on sales performance. By adopting a multi-level approach, we offer more granular insights into the role of capabilities, their interaction and their differential performance effects. The results of mediation and moderation analyses conclude that capabilities trigger a chain of effects, having impact on sales performance via innovation performance.

INTRODUCTION

At the core of the resource-based view of the firm (RBV) is the premise that organisational capabilities lead to enhanced performance (Barney 1991; Wernerfelt 1984). Although a significant body of empirical literature has provided support for this (e.g. Karna et al. 2016), the majority of studies have taken a macro-level perspective and investigated the effects of organisational capabilities on aggregated firm performance. In particular, empirical research explaining why organisational capabilities positively relate to value creation within firms remains scarce (e.g. Newbert 2008). Instead studies have focused on examining the direct relationship between capabilities and organisational performance which are likely to generate disparate empirical findings and theoretical conclusions. Consequently, there have been calls for more research explicitly disaggregating firm performance into financial and non-financial measures

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[44] The above entitled manuscript was submitted for review and publication consideration for the "'Theories from the Lab' - How Research on Science Commercialization Can Contribute to Management Studies" Special Issue of the Journal of Management Studies on October 7, 2016.

(Ethiraj et al. 2005) and integrating moderation and mediation analyses (Ray et al. 2004) to explain the boundary conditions of the RBV. Additionally, the literature on competitive advantage is lacking the understanding of micro-foundations of organisational capabilities—micro-macro links clarifying how individual capabilities interact within organisations in an aggregated fashion (Barney and Felin 2013). Therefore, our primary focus is to understand the process that conditions the impact of capabilities on performance.

To respond to a recent call in the literature to understand the micro-foundations of capabilities (Coff and Kryscynski 2011; Foss 2011), we elucidate the explanatory and predictive adequacy of explanations underlying the micro-foundations of capabilities by investigating the micro-macro interactions of individual-level and firm-level capabilities. We distinguish between entrepreneurial action and entrepreneurial outcome constructs by disaggregating firm-level performance effects into process-related and outcome-related performance. By drawing on the contingency view of the RBV, we propose that entrepreneurial process-related performance is a mechanism through which capabilities affect entrepreneurial outcomes. In line with this hypothesis, we investigate whether innovation performance, an intermediary competitive advantage, is a contingency that has a mediating or moderating role in the capabilities-sales performance relationship. Our paper therefore develops a multi-level approach to clarify a non-direct nature of the nomological network of relationships underpinning the capabilities-performance link.

THEORY AND HYPOTHESES

The conceptual model in Figure 1 depicts a set of relationships between capabilities, innovation performance and sales performance. The model distinguishes between the "backbone" direct relationships and hypothesised indirect relationships between all three capabilities and performance outcomes. The "backbone" direct relationships have been extensively examined in prior studies and there tends to be agreement in the literature that R&D capability, managerial capability and intellectual capability of a scientific team tend to have a positive effect on innovation and sales performance while interactions of capabilities tend to have a complementarity effect on innovation and sales performance (e.g. Deeds et al. 1999; Arora and Nandkumar 2012).

The primary objective of the paper is to understand the mechanism behind the capability-performance link. Therefore, the study takes the direct "backbone" relationships as a theoretical given and instead focuses on developing the hypotheses concerned with the indirect effect of capabilities on sales performance. The expectation is that capabilities per se may not be sufficient to explain the differences in firms' commercial performance, as suggested by many RBV studies (e.g. Henderson and Cockburn 1994; Arora and Nandkumar 2012). Rather, we conjecture that the role of capabilities is transitioned through and magnified by the innovation process. This role is modelled through the form of mediation and moderation: the positive effect of capabilities on sales performance is enabled or conditioned by innovation performance.

Hypothesis 1: Innovation performance mediates the effect of (a) R&D capability, (b) managerial capability, and (c) PI's intellectual capability on sales performance.

Hypothesis 2: Innovation performance increases the positive effect of (a) R&D capability, (b) managerial capability, and (c) PI's intellectual capability on sales performance.

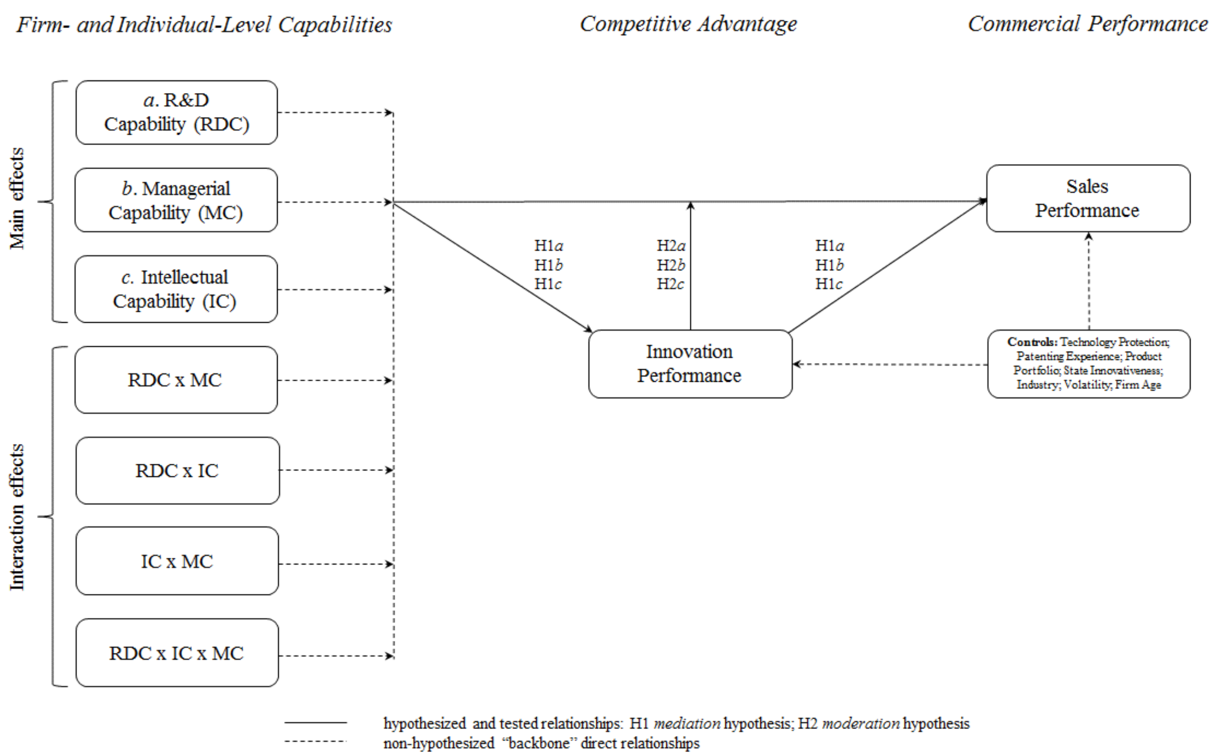

Figure 1. A conceptualisation of the mediating and moderating relationships of innovation performance

METHODS

We test our hypotheses using multi-level, multi-source data on 367 projects from 275 firms that participated in the Small Business Innovation Research (SBIR) program administered by the National Health Institute in the U.S. from 2006 to 2012. Consistent with the 'resource deployment' logic, we adopt the input-output approach to operationalise capabilities and model firm's activities as a transformation function of operational resources into practical objectives using stochastic frontier estimation (SFE) technique (Dutta et al. 1999). Three capabilities examined in this study refer to distinct elements of the entrepreneurial process: intellectual capability of the PI reflects an input, R&D capability relates to the technological activity, whereas managerial capability captures the potential for output. The results of structural equation modelling (SEM) show that the effect of R&D, managerial and the Principal Investigator's (PI) intellectual capability on sales performance is partially mediated by innovation performance, which is strongest for managerial capability. Also, innovation performance moderates the positive effect of managerial capability on sales performance.

DISCUSSION

Overall, our findings suggest that innovation performance is an underlying mechanism as well as a condition that affects the relationship between capabilities and sales performance. We offer fine-grained insights for the strategic management and entrepreneurship domains by demonstrating that it is not the mere possession of particular types of capabilities or their unique bundling that enhance firm's commercialisation performance. Rather, it is the indirect effect of capabilities via an intermediary competitive advantage that leads to firm performance. Consequently, our results provide a more nuanced understanding of the contingency perspective of the RBV. From this, we derive a series of research implications and provide valuable managerial implications for decision-making.

CONCLUSION

The main contribution of our paper is that it clarifies that the impact of capabilities in enhancing firm performance is contingent upon the intermediary competitive advantage that it creates. Overall, the results imply that the access to and possession of valuable, rare, inimitable and non-substitutable capabilities is insufficient to directly enhance firm's performance. Rather, it is the efficient deployment of their combinations in a way that creates economic value and results in competitive advantage that then leads to performance improvements. From the practical perspective, our study outlines two primary implications. First, patenting of inventions is a potentially lucrative strategy that enables small firms to use available capabilities to make an economic contribution. Second, managerial capability is a higher-order factor that links together all critical inputs and shapes the trajectory of their exploitation. Broadly speaking, our study indicates that small research-intensive firms pursuing commercialisation of their scientific effort benefit most from their unique capabilities when they make innovation activity central to their strategy, and nurture the capability of the manager to recognise opportunities and implement strategic change.

Table 1. Summary of measures

Variable	*Level of Analysis*	*Operationalisation*	*Measurement*	*Source*	*Transformation*
Sales performance	Firm	Firm sales by employee	Firm sales in t_{2014}, $ million divided by the number of employees in t_{2014}	Hoover's Online; firms' LinkedIn profiles, Bloomberg Business Week, ZoomInfo, Manta, Find the Company, SalesSpider, PrivCo, CorporationWiki	$\log_{10}(1+x)$
Innovation performance	Firm	Patent applications	Patent application stock in the period from t until t_{2014}	Patbase & Espacenet	$\log_{10}(1+x)$
R&D capability	Firm	SFE Equation: Output (Invention Activity) = Input 1 (Quality-Adjusted Patenting Output) + Input 2 (Knowledge Breadth) + Input 3 (PI's Intellectual Capability)	(1) Invention activity = total number of patent applications by firm in year t (2) Quality-adjusted global patenting output = citation-weighted patent stock by firm in year <t (3) Knowledge breadth = total number of patent classes firm has acquired in year <t (4) PI's intellectual capability = efficiency scores derived from stochastic frontier analysis (specification of the measure outlined below)	Patbase & Espacenet (1, 2, 3); SFE (4)	None
Managerial capability	Manager	SFE Equation: Output (Innovation Reach) = Input 1 (Commercial experience) + Input 2 (Intellectual Competence)	(1) International diversification= total number countries where the firm was granted patents in <t (2) Commercial experience= total number of years of manager's experience in commercial positions in any sector in <t (3) Inventive capacity = total number of patent applications by the manager in year <t	Patbase & Espacenet (1, 3); LinkedIn ZoomInfo Bloomberg Business Week (3)	None
PI's Intellectual capability	Principal investigator	SFE Equation: Output (Academic Impact) = Input 1 (Quality-Adjusted Academic Competence) + Input 2 (Knowledge Appropriation) + Input 3 (Intellectual Competence)	(1) Academic impact = h-index of the principal investigator defined by Scopus in year t (2) Quality-adjusted academic competence = citation-weighted publications of the principal investigator in year <t (3) Knowledge appropriation = ratio of self-citations by total documents published by the principal investigator in year <t (4) Inventive capacity= total number of patent applications by the principal investigator in year <t	Elsevier's Scopus (1, 2, 3); Patbase & Espacenet (4)	None
R&D X Managerial capability	Firm & Manager	Interaction of R&D and managerial capabilities	Multiplication of mean-centred variables	SFE	None

R&D X Intellectual capability	Firm & Principal investigator	Interaction of R&D and PI's intellectual capabilities	Multiplication of mean-centred variables	SFE	None
Intellectual X Managerial capability	Principal investigator & Manager	Interaction of PI's intellectual and managerial capabilities	Multiplication of mean-centred variables	SFE	None
Technology protection	Firm	The propensity to increase or decrease the patenting activity	The difference between the number of patent applications in time t-1 and t-2	Patbase & Espacenet	None
Patenting experience	Firm	Years of patenting	Number of years since the first filed patent until the award date t	Patbase & Espacenet	$\log_{10}(1+x)$
Success-adjusted product portfolio breadth	Firm	The number of SBIR-funded projects in the pipeline	The number of SBIR-funded projects in the pipeline for a 3-year window (t, t-1, t-2), weighted by the amount of financial support (in million dollars) received in the corresponding 3-year window	SBIR data	$\log_{10}(1+x)$
State innovativeness	Environment	Innovation Scores of US States	The ranking list retrieved from Bloomberg's Visual Data platform	Bloomberg	None
Industry volatility (2014)	Environment	Industry volatility for a 5-year rolling window, lagged by 1 year	Industry stock return volatility computed as standard deviation from average annual equal-weighted returns of the Fama and French (1997) 49 industries	Ken French Data Library	None
Firm age	Firm	Firm age at project start	Number of years, count	Company website; Bloomberg Business Week	$\log_{10}(1+x)$
Project cohort	Project	Year of Phase I award, dummy	Coding: 2006 = 1; 2007 = 2; 2008 = 3; 2009 = 4; 2010 = 5; 2011 = 6 2012 = 7	SBIR data	None

Table 2. Structural equation modelling (SEM) results – direct effect models[a]

	Model 1				*Model 2*			
	Innovation Performance		*Commercial Performance*		*Innovation Performance*		*Commercial Performance*	
	Coefficient	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*
Direct effects								
R&D capability (RDC)	0.17	3.47***	0.04	0.83	0.11	1.56	0.04	0.48
Managerial capability (MC)	0.29	4.11***	0.21	2.96***	0.15	1.18	0.14	1.23
Intellectual capability (IC)	0.12	2.61***	-0.07	-1.25	0.18	3.41***	-0.04	-0.65
Interaction effects								
RDCxMC					0.08	0.85	0.05	0.55
RDCxIC					0.06	0.78	-0.01	-0.17
ICxMC					0.22	2.11**	0.13	1.25
RDCxICxMC					-0.13	-1.31	-0.08	-0.80
Control variables								
Technology protection	0.07	1.58	0.01	0.19	0.07	1.58	0.01	0.26
Patenting experience	0.10	1.38	-0.10	-1.29	0.11	1.52	-0.10	-1.14
Success-adjusted product portfolio breadth	0.20	3.79***	0.25	3.68***	0.20	3.94***	0.25	3.71***
State innovativeness	0.10	2.15**	-0.03	-0.55	0.09	1.95*	-0.03	-0.63
Industry volatility	-0.04	-0.65	-0.18	-1.65	-0.07	-1.06	-0.19	-1.70
Firm age	-0.08	-1.44	0.27	3.69***	-0.10	-1.79*	0.26	3.45***
F-Value[b]	14.36***		8.90***		9.05***		6.39***	
R^2	0.28		0.25		0.30		0.25	
Adjusted R^2	0.26		0.23		0.27		0.23	

[a] n= 367; *** p<0.01; ** p<0.05; * p<0.1
[b] F-Value, R^2 and Adjusted R^2 refer to individual equations

Table 3. Structural equation modelling (SEM) results – indirect effect models[a]

	Model 3				*Model 4*			
	Innovation Performance		*Commercial Performance*		*Innovation Performance*		*Commercial Performance*	
	Coefficient	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*
Direct effects								
R&D capability (RDC)	0.17	3.47***	0.00	-0.02	0.16	3.44***	0.02	0.45
Managerial capability (MC)	0.29	4.11***	0.14	1.90*	0.29	3.99***	0.06	1.08
Intellectual capability (IC)	0.12	2.61***	-0.10	-1.82*	0.13	2.80***	-0.08	-1.46
Mediating effect								
Innovation performance (IP)			0.26	4.41***				
Moderating effect								
Innovation performance							-0.05	-0.14
IPxRDC							0.10	0.78
IPxMC							0.29	3.21***
IPxIC							-0.11	-0.83
Control variables								
Technology protection	0.07	1.58	-0.01	-0.22	0.07	1.58	-0.02	-0.40
Patenting experience	0.10	1.38	-0.13	-1.66	0.10	1.40	-0.07	-0.80
Success-adjusted product portfolio breadth	0.20	3.79***	0.20	3.02***	0.19	3.77***	0.19	2.44**
State innovativeness	0.10	2.15**	-0.06	-1.08	0.10	2.17**	-0.03	-0.62
Industry volatility	-0.04	-0.65	-0.17	-1.58	-0.04	-0.63	-0.15	-1.45
Firm age	-0.08	-1.44	0.29	4.07***	-0.08	-1.42	0.28	3.66***
F-Value[b]	14.36***		10.23***		14.36***		10.47***	
R^2	0.28		0.30		0.28		0.31	
Adjusted R^2	0.26		0.28		0.26		0.29	

[a] n= 367; *** p<0.01; ** p<0.05; * p<0.1
[b] F-Value, R^2 and Adjusted R^2 refer to individual equations

Paper 2

Evaluating Innovation Investment Outcomes of Government Venture Funding in the U.S.: Real Options Perspective[45]

ABSTRACT

This study examines the role of government venture funding in facilitating entrepreneurship and innovation. We draw upon real options reasoning (ROR) theory to understand the effects of various resource allocation strategies on investment yield. To investigate government investment patterns, 367 projects that participated in the Small Business Innovation Research program in the U.S. were analysed over a seven-year period. We find that the formal ROR structure evident in the composition and execution of the government venture funding programme is only intuitively underpinned by the real options logic of decision-making. The results reveal that high initial funding commitment and continuation of funding have a diminishing effect on return on investment, whereas consistent matching of funding decisions in line with ROR allows extracting value from staged investments.

INTRODUCTION

Small and medium enterprises (SMEs) significantly contribute to employment and innovation creation, but their role in fostering the economic growth is less prominent due to limited access to finance. To address market imperfections, governments of major economies initiate high-budget publicly-funded financing programmes to support entrepreneurship and innovation. Although there is generally a wide consensus on the appropriateness of government intervention to stimulate the SME sector, the evidence on the effects of public funds to subsidise R&D efforts of small firms remains inconsistent. We respond to a call for more studies evaluating the effectiveness and limitations of government funding initiatives (Pavitt 1998; Bayona-Saez and Garcia-Marco 2010). We develop a conceptual approach to move beyond the sheer assumptions of the importance of budget as an input to the innovation process and instead examine how resources can be allocated in the most optimal way to yield performance benefits, making a contribution to the literature on strategic management of investment portfolios. We use real options theory to examine the outcomes of the staged government funding scheme, under which initial

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investment is characterised as a real option that grants investors the right to make further investment or to discontinue funding. The options approach has been described as a useful strategic tool in making resource commitments with the minimal risks (Chatterjee et al. 1999). We explore to what extent the implementation of investment resource allocation strategies in line with prescriptions of real options logic offers performance advantages in the context of government venture funding. The results imply that the consistent implementation of the options approach offers significant benefits to developing the optimal investment procedures in the strategy field.

THEORY AND HYPOTHESES

The essence of real options reasoning is expressed in its proposed approach for informing resource allocation decisions in organisations, which is built on a number of fundamental assumptions intended to guide the logics of such processes (Adner 2007). These assumptions concern two types of decisions—initial resource allocation and subsequent resource reallocation, and the correspondence of these decisions distinguishes real options decision-making from sequential decision-making (Adner and Levinthal 2004b; Adner and Levinthal 2004a; Adner 2007). Therefore, to differentiate between a coherent and disciplined decision-making prescribed by real options reasoning and a path-dependent decision-making under other sequential approaches, it is important to disentangle distinct elements comprising resource allocation processes (Adner 2007; Klingebiel and Adner 2015). From the review of extant literature, constructs relevant to a strategic theory of investment incorporating ROR were identified as initial commitment, discontinuation and sequencing. Literature indicates that real options approach matches these elements in a way that allows to distinguish it from other resource allocation regimes (Klingebiel and Adner 2015). The primary objectives pursued by the government investment programmes are to increase commercialisation, encourage entrepreneurship and stimulate innovation. To reflect this, anticipated performance outcomes of real options investments were conceptualised along three dimensions as post-funding sales performance, employment creation and innovation activity, and expressed from the funders' perspective as yield on investment.

To sum, in line with previous literature (Klingebiel and Adner 2015), the study proposes that distinct elements of real options reasoning—initial funding commitment, funding continuation, funding sequencing, and fit of funding decisions—might have differential effects on investment yield. The conceptual model in Figure 1 depicts a set of hypotheses consistent with the expectations that the presence of ROR in investment decisions will be reflected in a propensity to keep initial commitment and sequencing low to minimise downside risks, and to continue projects with high initial commitment and discontinue projects with low initial commitment. The links between different elements of ROR and anticipated performance outcomes are expressed in a series of hypotheses.

Hypothesis 1: The magnitude of initial funding commitment has a negative effect on investment yield—(a) sales yield, (b) employment yield, and (c) innovation yield.

Hypothesis 2: Funding discontinuation has a negative effect on investment yield—(a) sales yield, (b) employment yield, and (c) innovation yield.

Hypothesis 3: Fit of funding decisions, i.e. low initial funding commitment and discontinuation or high initial commitment and continuation, has a positive effect on investment yield—(a) sales yield, (b) employment yield, and (c) innovation yield.

Hypothesis 4: For firms with prior awards, high rate of funding sequencing has a negative effect on investment yield—(a) sales yield, (b) employment yield, and (c) innovation yield.

Hypothesis 5: The performance effect of fit of funding decisions is greater at the at the cumulated portfolio level than at the individual option level.

Hypothesis 6: An opening of a new individual project has a positive effect on investment yield—(a) sales yield, (b) employment yield, and (c) innovation yield of firms with no prior awards, but an addition of a new individual project to the portfolio of firms with prior awards has no effect.

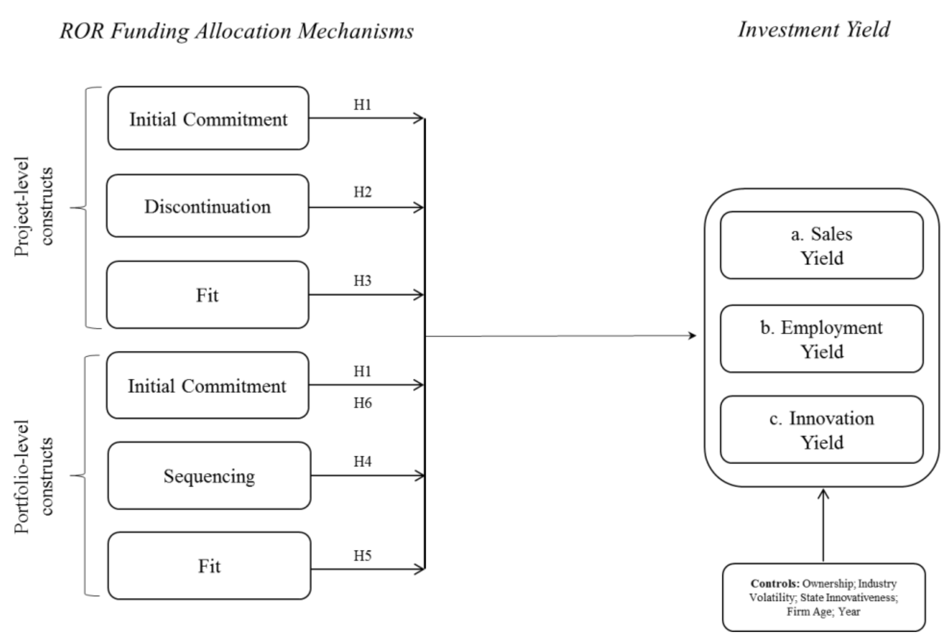

Figure 1. Conceptual model

METHODS

To examine the outcomes of government venture funding, we analysed performance of projects that received financial support under the SBIR program. The SBIR initiative is structured in phases and therefore represents a suitable context for testing our hypotheses. We propose that the SBIR venture funding programme follows the explicit ROR structure, whereby government funders sequence the process of potential value creation. First, funders invest in a number of Phase I projects and thereby create a portfolio of options, with the right to defer further investments in those options until a major part of uncertainty about their viability has been resolved. When Phase I awardees apply for Phase II funding, investors have to decide whether to exercise or abandon the option. The results of the seemingly unrelated regression (SUR) simultaneously validate a direct positive impact of real options logic and delineate its boundary conditions in the context of government venture funding.

DISCUSSION

The findings show that when venture capitalists allocate financial resources in line with real options decision-making logic, they gain significant improvements in performance outcomes, whereas deviations from prescriptions of ROR potentially detract from the value offered by a flexible options-like approach. Most importantly, the results indicate that the value offered by the government funding programmes gets eroded due to inefficient funding allocation decisions, whereby an additional unit of government investment does not lead to better stream of social value from the private sector. The value from the investment process can be extracted when positioning trial commitments are small, and follow-up funds are allocated to selected projects only. That is, discontinuation decision has to be exercised in a disciplined manner. It can be concluded that the overall positive effects of allocated funding on investment yield tend to decrease the more money or, the more grants the firms receive.

CONCLUSION

The present study offers a set of insights that may help increase the effectiveness of sequential investment decision-making. This study's notable implication suggests that government venture programmes like the SBIR should be structured in such a way that (i) early-stage awards are low-cost and offered to a larger number of participants, and (ii) later-stage awards are allocated to participants with no other options in the portfolio. The primary idea behind the proposition is that first-time participants of the programme should be given priority over multiple-award holders.

Table 1. Summary of measures

Variable	***Level of Analysis***	***Operationalisation***	***Measurement***	***Source***	***Transformation***
Sales yield	Firm	$ Million	Firm sales in t_{2014} divided by total prior investment ($ million in $\sum_{t,\, t-1 \ldots t-n}$)	Hoover's Online, SBIR data	$\log_{10}(1+x)$
Employment yield	Firm	Headcount	Number of employees in t_{2014}, divided by total prior investment ($ million in $\sum_{t,\, t-1 \ldots t-n}$)	Hoover's Online, SBIR data	$\log_{10}(1+x)$
Innovation yield	Firm	Patent applications	Patent application stock in the period from t until t_{2014} divided by total prior investment ($ million in $\sum_{t,\, t-1 \ldots t-n}$)	Patbase & Espacenet, SBIR data	$\log_{10}(1+x)$
Initial commitment (project-level funding)	Project	Success magnitude: $ amount of Phase I award granted to an individual project in the database	Number retrieved from the SBIR database	SBIR data	$\log_{10}(1+x)$
Initial commitment (project-level funding)	Project	Success magnitude: $ amount of Phase I award granted to an individual project in the database, dummy. Low initial commitment: <mean High initial commitment: >=mean	Coding: Low initial commitment = 1 High initial commitment = 0	SBIR data	none
Discontinuation (project-level funding)	Project	Phase II outcome: whether or not Phase I project in the database later received Phase II funding, dummy	Coding: Discontinue = 1 Continue = 0	SBIR data	none
Fit (project-level funding)	Project	Fit is an interaction of initial commitment and reallocation. Low initial commitment: <mean High initial commitment:- >=mean	Coding: Low initial commitment x Discontinue / High initial commitment x Continue = 1 (fit) High initial commitment x Continue / Low initial commitment x Discontinue = 0 (no-fit)	SBIR data	none
Initial commitment (portfolio-level funding)	Portfolio	Average $ amount the firm received for cumulated prior Phase I awards	E.g., if the firm received a total of $0.75 million for 7 Phase I awards, then average prior Phase I $ award is 0.75/7=0.11	SBIR data	$\log_{10}(1+x)$
Initial commitment (portfolio-level funding)	Portfolio	Average $ amount the firm received for cumulated prior Phase I awards, dummy. Low initial commitment: <mean High initial commitment: >=mean	Coding: Low initial commitment = 1 High initial commitment = 0	SBIR data	none
Sequencing (portfolio-level funding)	Portfolio	Phase II transition rate: a ratio of a number of received Phase II awards per Phase I awards	E.g., if the firm received 2 Phase II awards and 10 Phase I awards, then the Phase II transition rate is 2/10=0.2	SBIR data	$\log_{10}(1+x)$

Fit (portfolio-level funding)	Portfolio	Fit is an interaction of initial commitment and reallocation. Low initial commitment: <mean High initial commitment: >=mean Discontinue: Phase II transition rate = 0 Continue: Phase II transition rate > 0	Coding: Low initial commitment x Discontinue / High initial commitment x Continue = 1 (fit) High initial commitment x Continue / Low initial commitment x Discontinue = 0 (no-fit)	SBIR data	none
Non-woman-owned	Firm	Whether or not the firm is woman-owned, dummy	Coding: Non-woman-owned = 1 Woman-owned = 0	SBIR data	None
Non-minority-owned	Firm	Whether or not the firm is minority-owned, dummy	Coding: Non-minority-owned = 1 Minority-owned = 0	SBIR data	None
Non-HubZone-owned	Firm	Whether or not the firm is HubZone-owned, dummy	Coding: Non-HubZone-owned = 1 HubZone-owned = 0	SBIR data	None
State innovativeness	Environment	Innovation Scores of US States	The ranking list retrieved from Bloomberg's Visual Data platform	Bloomberg	None
Industry volatility (2014)	Environment	Industry volatility for a 5-year rolling window, lagged by 1 year	Industry stock return volatility computed as standard deviation from average annual equal-weighted returns of the Fama and French (1997) 49 industries	Ken French Data Library	None
Firm age	Firm	Firm age at project start	Number of years, count	Company website; Bloomberg Business Week	$\log_{10}(1+x)$
Project cohort	Project	Year of Phase I award, dummy	Coding: 2006 = 1; 2007 = 2; 2008 = 3; 2009 = 4; 2010 = 5; 2011 = 6 2012 = 7	SBIR data	None

Table 2: System of equations (SUR) results – full sample

	Equation 1		*Equation 2*		*Equation 3*	
	Sales Yield		*Employment Yield*		*Innovation Yield*	
	Coefficient	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*
Independent variables:						
Project-level constructs						
Initial commitment	-0.19	-3.62***	-0.24	-4.51***	-0.06	-1.23
Discontinuation	-0.06	-0.52	-0.06	-0.51	-0.16	-1.40
Fit	-0.11	-0.93	-0.13	-1.22	-0.02	-0.18
Portfolio-level constructs						
Fit	0.28	2.40**	0.31	2.81***	0.14	1.27
Control variables:						
Non-woman-owned	0.45	1.51	0.46	1.93	0.20	0.99
Non-minority-owned	-0.11	-0.28	-0.23	-0.71	0.38	1.33
Non-HubZone-owned	-0.41	-1.60	-0.52	-2.02**	-0.18	-0.75
Industry volatility	-0.21	-2.66***	-0.12	-1.61	0.03	0.36
State innovativeness	-0.05	-0.96	-0.06	-1.12	0.04	0.79
Firm age	0.02	0.32	-0.11	-2.04**	-0.18	-3.34***
Year dummies	Incl.		Incl.		Incl.	
R^2	0.12		0.15		0.09	
Adjusted R^2	0.08		0.12		0.05	

N= 367

*** p<0.01; ** p<0.05; * p<0.1

Table 3: System of equations (SUR) results – cluster with no prior awards

	Equation 1		*Equation 2*		*Equation 3*	
	Sales Yield		*Employment Yield*		*Innovation Yield*	
	Coefficient	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*
Independent variables:						
Project-level constructs						
Initial commitment	-0.43	-3.75***	-0.41	-4.76***	-0.09	-0.61
Discontinuation	-0.35	-1.68*	-0.27	-1.74*	-0.50	-1.88*
Fit	0.21	1.10	0.22	1.55	0.13	0.51
Control variables:						
Non-woman-owned	0.46	0.95	0.68	2.23**	0.00	0.00
Non-minority-owned	-0.08	-0.11	-0.24	-0.52	0.80	1.15
Non-HubZone-owned	-0.11	-0.28	-0.20	-0.69	-0.26	-0.58
Industry volatility	-0.21	-1.26	-0.06	-0.49	0.10	0.71
State innovativeness	0.03	0.26	0.02	0.25	0.08	0.67
Firm age	0.49	4.30***	0.37	4.30***	-0.06	-0.49
Year dummies	Incl.		Incl.		Incl.	
R^2	0.37		0.41		0.13	
Adjusted R^2	0.28		0.33		0.01	

N= 128

*** p<0.01; ** p<0.05; * p<0.1

Table 4: System of equations (SUR) results – cluster with prior awards

	Equation 1		*Equation 2*		*Equation 3*	
	Sales Yield		*Employment Yield*		*Innovation Yield*	
	Coefficient	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*
Independent variables:						
Project-level constructs						
Initial commitment	-0.03	-0.69	-0.08	-1.66	-0.02	-0.37
Discontinuation	0.07	0.65	0.03	0.28	-0.02	-0.21
Fit	-0.02	-0.16	-0.07	-0.66	0.01	0.11
Portfolio-level constructs						
Initial commitment	-0.13	-2.19**	-0.15	-2.40**	-0.11	-2.01**
Sequencing	-0.19	-3.96***	-0.24	-4.95***	-0.15	-3.21***
Fit	0.17	1.74*	0.15	1.43	0.14	1.46
Control variables:						
Non-woman-owned	0.10	0.37	0.02	0.08	0.23	1.39
Non-minority-owned	0.01	0.03	-0.11	-0.37	0.34	1.39
Non-HubZone-owned	-0.24	-0.95	-0.39	-1.40	0.10	0.40
Industry volatility	-0.07	-0.69	0.01	0.08	-0.01	-0.12
State innovativeness	0.00	0.03	0.01	0.14	0.04	0.90
Firm age	0.08	1.31	0.04	0.69	-0.09	-1.46
Year dummies	Incl.		Incl.		Incl.	
R^2	0.16		0.18		0.13	
Adjusted R^2	0.10		0.12		0.06	

N= 239

*** p<0.01; ** p<0.05; * p<0.1

Paper 3

Analysing Perceived and Actual Effects of Public Venture Capitalists' Selection Criteria on Firm Performance: Signalling Perspective[46]

ABSTRACT

Under conditions of information asymmetry, markets attend to observable characteristics of firms to infer their unobservable but desirable attributes(Sanders and Boivie 2004). Therefore, forming investor opinion around positive competences is critical to the success of nascent ventures in obtaining capital. We examine which characteristics of firms, projects and individuals are perceived as signals of quality, or lack thereof, and influence decisions of government venture capitalists to allocate or withdraw funding. Specifically, by leaning on signalling theory we outline categories of factors that influence investors' perceptions during the evaluation process. We find that public investors' decision-making is subject to evaluation bias and inefficiency, reflected in the discrepancies between the perceived and actual impact of selection criteria on firms' performance.

INTRODUCTION

Signals communicate useful information about economic agents' underlying qualities. However, interpretation of signals can be complicated by contextual factors as well as recipients' experience and frames of reference. In particular, interpretation of signals transmitted by firms operating in nascent or niche industries is problematic. The early years of nascent firms are characterised by fluid entrepreneurial processes which emerge as a result of learning-by-doing. Thus, task uncertainty, defined as the discrepancy between required information and possessed information necessary to perform a task (Sapienza and Gupta 1994), is greater for early-stage ventures working on highly innovative projects.

Such emergent nature of entrepreneurial practices coupled with task uncertainty makes it difficult to define ex-ante the desired list of skills and abilities of economic players in nascent industries, further magnifying information asymmetry(Zahra and Filatotchev 2004). Given that emerging industries face greater unresolved uncertainties, evaluators try to project their future course of development by relying on memories of historical performance of established industries (Zahra and Filatotchev 2004). However, overreliance on prior knowledge may lead to misconceptions and subsequent misinterpretation of signals.

[46] The above entitled manuscript is to be submitted for review and publication consideration to the Journal of Business Venturing.

Ambiguity involved in new ventures' evaluation makes investors predisposed to heuristics and biases. One of the most prevalent biases in investment context is that of overconfidence, which can be manifested in the increased propensity to overestimate the likelihood of occurrence of future outcomes or validity of own knowledge, resulting in impaired decision-making (Griffin and Varey 1996). Zacharakis and Shepherd (2001) showed evidence that overconfidence negatively affects venture capitalists' decision accuracy. Among other factors, the authors found that overconfidence can surge when decision-makers automatically process familiar information relevant to the decision and refrain from questioning existing knowledge and seeking new information (Zacharakis and Shepherd 2001). A study by Shepherd (1999) also provided empirical evidence that the accuracy of venture capitalists' introspection is limited.

Organisational research on behavioural theories has made progress towards understanding decision-making processes underpinning innovation investment outcomes. Still, more research is needed to examine the correspondence of the theory with decision-making practices, accounting for heuristics and biases inherent in the process (Scherpereel 2008). Our objective is to understand the evaluation process and selection criteria that public capital investors follow to allocate funding to candidates. Additionally, we examine the investors' ability in distilling high-profile candidates. We analyse investors' decision-making accuracy by comparing the effects of candidates' characteristics that were used as important selection criteria on desired performance outcomes. In sum, the expectation is that there is a discrepancy between expected and real association of firms' attributes with anticipated performance outcomes, which adversely affects decision accuracy and subsequently upside potential of investments.

THEORY AND HYPOTHESES

In line with entrepreneurship research, we focus on legitimacy characteristics pertaining to the manager and the principal investigator, project attributes and firm's efficacy. The logic for selecting these constructs is that legitimacy attributes are relevant to the intangible assets necessary to proceed in innovation activity, project attributes are relevant to the individual R&D proposition, while efficacy is relevant to the activities of the firm as a whole as well as the viability of the R&D project to reach the commercialisation stage. The first proposition is that TMTs' different characteristics signal their legitimacy which minimises investors' uncertainty in firms' underlying quality. TMT legitimacy was conceptualised as a cumulative function of (i) role legitimacy, (ii) resource legitimacy and (iii) intellectual legitimacy (Cohen and Dean 2005; Higgins and Gulati 2006). The underlying reasoning is that types of previous experience, advanced qualifications, affiliations with educational institutions and productive output of TMT members are associated with higher quality firms and enhance investors' perceptions of legitimacy. Second, we assert that certain types of projects will be perceived as more appealing based on evaluators' expectations and perceptual filters. As a result, projects will be selected by their scope and category. Third, we expect signals that convey up-to-date information to be perceived as particularly strong and reliable by investors (Janney and Folta 2006) as they indicate firms' intentions and abilities (DeKinder and Kohli 2008), such as organisational efficacy and performance in carrying out the R&D task. Figure 1 depicts a configuration of tested relationships between signals, their perceived effect (outcomes of investors' decision-making) and their actual effect (firm performance).

Hypothesis 1: Signals of role legitimacy, resource legitimacy and intellectual legitimacy have a positive effect on (a) the magnitude of initial funding commitment, (b) the likelihood of funding continuation, (c) sales performance, (d) employment performance, and (e) innovation performance.

Hypothesis 2: Project appeal characteristics have a positive effect on (a) the magnitude of initial funding commitment, (b) the likelihood of funding continuation, (c) sales performance, (d) employment performance, and (e) innovation performance.

Hypothesis 3: Signals of efficacy have a positive effect on (b) the likelihood of funding continuation, (c) sales performance, (d) employment performance, and (e) innovation performance.

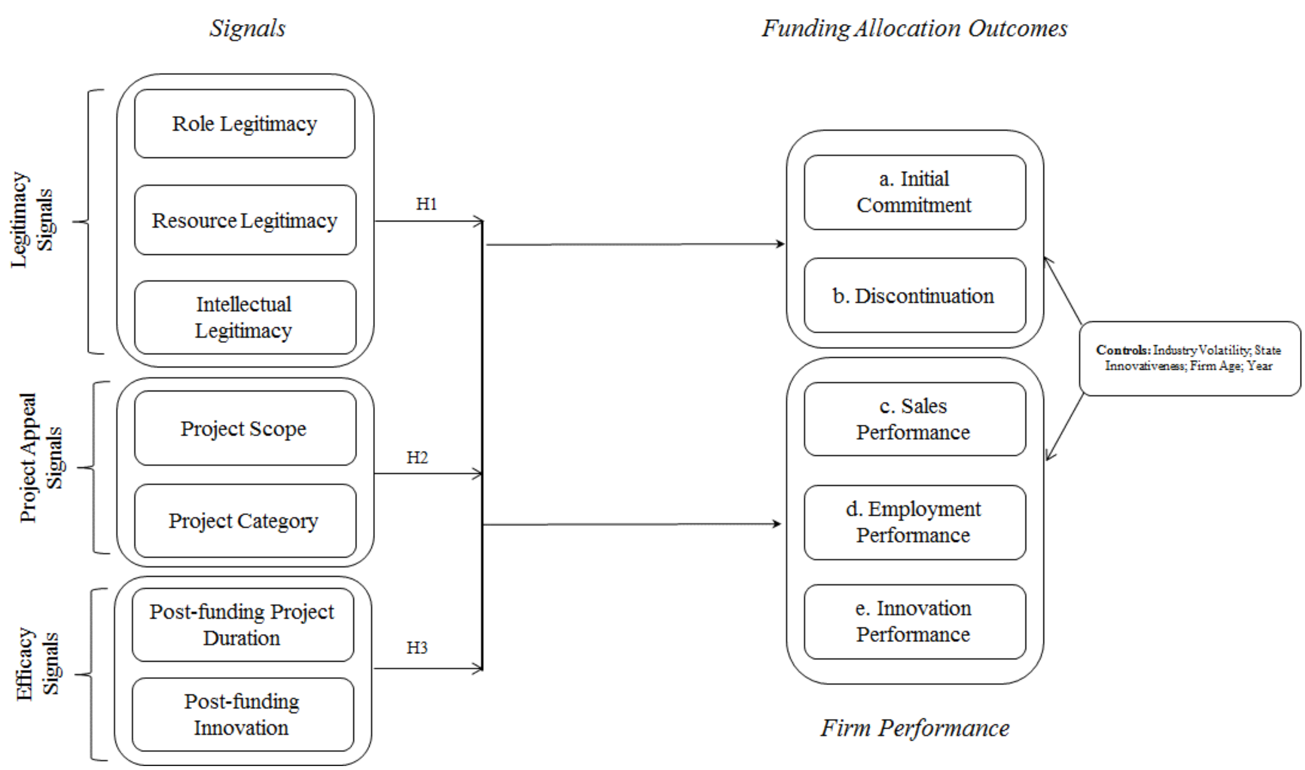

Figure 1. Conceptual model

METHODS

Signalling occurs in the staged investment process of the government venture capital programme. At t=0, firms include specific information in a funding application form to signal their underlying abilities. To resolve information asymmetry, investors evaluate attributes of the applicants based on evidence included in the application narratives, and their perceptions of firms' and projects' potential is reflected in the variation of monetary sizes of awards. At t=2, in addition to already known attributes of applicants, investors also have access to post-Phase I interim information, that can help draw further conclusions about firms' or projects' potential for future payoffs, which results in the decision to continue or discontinue subsequent funding. We retrieved a list of scored review criteria used by government venture capital decision-makers when assessing new applications for funding. Then, we matched them with their corresponding theoretical counterparts derived from the extant literature to reflect the investment logic.

DISCUSSION

Overall, the results demonstrate that although some signals are directionally correct, others are ignored as important antecedents of performance, suggesting the presence of the misinterpretation bias. Role-experience and role-commitment alignments within the team have important implications for performance. Efficacy is generally associated with performance outcomes, making it an important signal at Phase II evaluation stage, whereas project appeal characteristics are crude signals.

CONCLUSION

The study offers insights into the decision-making process of government venture capital providers. The findings suggest that there is an element of mismatch between the expected and actual impact of selection criteria on performance. Deficient criteria indicate that investors may have limited mechanisms in place to accurately evaluate the value of R&D projects. Developing selection criteria based on factors that predict venture's success would minimise the evaluation bias and help decision-makers differentiate between high-achievers and under-achievers (Lerner 2002). The results also show that effects of characteristics are not universal across different indicators of firm's performance. Thus, the goal of the government programme to simultaneously increase commercialisation, encourage entrepreneurship and stimulate innovation might be unrealistic given the unique sets of resources that nascent ventures necessitate to achieve certain performance outcomes. The results imply that government funders cannot 'kill two birds with one stone' by using standardised evaluation methods. Therefore, a more fine-grained approach would help distil high-profile candidates from a pool of applicants.

Table 1. Summary of measures

Variable	*Level of Analysis*	*Operationalisation*	*Measurement*	*Source*	*Transformation*
Sales Performance	Firm	$ Million	Firm sales in t_{2014}, $ million	Hoover's Online	$\log_{10}(1+x)$
Employment Performance	Firm	Headcount	Number of employees in t_{2014}	Hoover's Online	$\log_{10}(1+x)$
Innovation Performance	Firm	Patent applications	Patents application stock in the period from t until t_{2014}	Patbase & Espacenet	$\log_{10}(1+x)$
Manager CEO PI CEO	Manager Principal investigator	Whether or not the person is a CEO at the award date t, dummy	Coding: CEO = 1 Non-CEO = 0	LinkedIn	None
PI's firm tenure	Principal investigator	Tenure with the firm at the award date t	Number of years, count	LinkedIn	None
Manager's technical experience PI's technical experience	Manager Principal investigator	Experience in technical positions in the same sector of the start-up before award date at t-1	Number of years, count	LinkedIn	None
Manager's entrepreneurial experience PI's entrepreneurial experience	Manager Principal investigator	Entrepreneurial experience in any sector before award date at t-1	Number of years, count	LinkedIn	None
Manager' elite education PI's elite education	Manager Principal investigator	A score of the last attended university from the Top 100 worldwide universities ranking at time t. Universities not in the top 100 received a score of zero	Scores retrieved from Academic Ranking of World Universities (ARWU)	Shanghai Ranking	None
Manager's MBA PI's MBA	Manager Principal investigator	Whether or not the person has an MBA degree at time t, dummy	Coding: MBA = 1 No MBA = 0	LinkedIn	None
Manager's PhD PI's PhD	Manager Principal investigator	Whether or not the person has a doctorate degree at time t, dummy	Coding: Dr = 1 Mr/Ms = 0	LinkedIn	None
Manager's professorship PI's professorship	Manager Principal investigator	Whether or not the person is a professor at time t, dummy	Coding: Professor = 1 Not Professor = 0	LinkedIn	None
Manager's patents PI's patents	Manager Principal investigator	How many patent applications the person had prior to award date at t-1	Number of patent applications, count	Patbase	$\log_{10}(1+x)$
Manager's publications PI's publications	Manager Principal investigator	How many published documents the person had prior to award date at t-1	Number of published documents, count (includes journal articles, conference papers, books, and other)	Scopus	$\log_{10}(1+x)$

Project duration	Firm	How much time elapsed between Phase I project start and project end date at time t	Number of days, count	SBIR data	None
Invention activity	Firm	How many patents applications the firm filed in a 3-year window following Phase I award (t+1, t+2, t+3)	Number of patent applications from Patbase, count	Patbase	$\log_{10}(1+x)$
Project scope	Project	Whether the project targets a specific cancer type or multiple at time t	Coding: Multiple cancer types targeted = 1 (broad) Specific cancer type targeted = 0 (narrow)	SBIR data	None
Project category	Project	Federal programme type by assigned category from the Catalogue of Federal Domestic Assistance (CFDA) at time t	Coding: Cancer Cause and Prevention Research = 1 Cancer Detection and Diagnosis Research = 2 Cancer Treatment Research = 3 Cancer Biology Research = 4	SBIR data	None
State innovativeness	Environment	Innovation Scores of US States	The ranking list retrieved from Bloomberg's Visual Data platform	Bloomberg	None
Industry volatility (2014)	Environment	Industry volatility for a 5-year rolling window, lagged by 1 year (2013)	Industry stock return volatility computed as standard deviation from average annual equal-weighted returns of the Fama and French (1997) 49 industries	Ken French Data Library	None
Industry volatility (t)	Environment	Industry volatility for a 5-year rolling window, lagged by 1 year (t-1)	Industry stock return volatility computed as standard deviation from average annual equal-weighted returns of the Fama and French (1997) 49 industries	Ken French Data Library	None
Firm age	Firm	Firm age at project start	Number of years, count	Company website; Bloomberg Business Week	$\log_{10}(1+x)$
Project cohort	Project	Year of Phase I award, dummy	Coding: 2006 = 1; 2007 = 2; 2008 = 3; 2009 = 4; 2010 = 5; 2011 = 6 2012 = 7	SBIR data	None

Table 2: Estimation results[47]

	Equation 1		*Equation 2*		*Equation 3*		*Equation 4*		*Equation 5*	
	Initial Commitment		*Discontinuation*		*Sales Performance*		*Employment Performance*		*Innovation Performance*	
	Coefficient	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*
Independent variables:										
Role legitimacy										
Manager CEO	-0.08	-0.62	-0.04	-0.11	-0.34	-2.58**	-0.34	-2.64**	-0.27	-2.22**
PI CEO	0.00	-0.02	-1.03	-3.15***	0.09	0.78	0.05	0.49	-0.02	-0.18
PI's firm tenure	-0.23	-2.62***	0.33	1.31	-0.19	-2.70***	-0.20	-2.95***	-0.04	-0.45
Manager's technical experience	-0.12	-1.28	0.25	1.02	-0.02	-0.31	-0.04	-0.59	0.11	1.00
PI's technical experience	0.11	1.50	-0.27	-1.14	-0.03	-0.43	-0.04	-0.55	-0.11	-1.51
Manager's entrepreneurial experience	-0.14	-1.60	-0.09	-0.33	0.03	0.30	0.01	0.07	0.04	0.41
PI's entrepreneurial experience	0.04	0.48	0.04	0.14	-0.12	-1.86*	-0.09	-1.41	-0.10	-1.32
Resource legitimacy										
Manager's elite education	0.13	1.51	0.04	0.20	0.13	1.76	0.12	1.58	0.19	3.24***
PI's elite education	-0.07	-0.86	0.11	0.60	-0.03	-0.38	0.02	0.24	-0.04	-0.56
Manager's MBA	-0.18	-1.04	0.07	0.15	-0.05	-0.35	0.03	0.20	-0.21	-1.14
PI's MBA	0.04	0.16	-1.24	-1.34	-0.27	-1.32	-0.25	-1.19	0.03	0.15
Manager's PhD	0.14	0.92	0.20	0.43	0.06	0.42	0.09	0.54	-0.17	-0.97
PI's PhD	-0.05	-0.14	-0.10	-0.13	-0.47	-1.20	-0.37	-1.15	0.04	0.18
Manager's professorship	0.13	0.76	-0.05	-0.11	-0.09	-0.73	0.01	0.10	0.04	0.31
PI's professorship	0.28	1.67	-0.47	-1.23	0.17	1.39	0.16	1.16	-0.26	-1.93*
Intellectual legitimacy										
Manager's patents	-0.10	-1.15	0.27	1.31	-0.11	-1.80*	-0.07	-0.99	-0.07	-1.00
PI's patents	0.16	2.28**	0.17	0.96	-0.01	-0.16	0.03	0.57	0.24	4.05***
Manager's publications	0.01	0.10	-0.28	-1.09	0.07	0.95	0.02	0.31	-0.02	-0.20
PI's publications	-0.19	-2.32**	-0.26	-1.36	0.04	0.61	0.05	0.87	0.15	2.14**
Efficacy										
Project duration			0.33	2.49**	-0.02	-0.55	-0.07	-1.43	-0.02	-0.38
Invention activity			-0.34	-1.96*	0.17	3.12***	0.20	3.57***		
Project Appeal										
Project_broad appeal	-0.28	-2.31***	0.05	0.15	-0.01	-0.12	0.05	0.35	-0.05	-0.50
Cancer Detection and Diagnosis Research	0.27	1.51	0.83	1.83*	0.25	1.53	0.17	1.19	0.46	2.91***
Cancer Treatment Research	0.22	1.22	0.78	1.74*	0.18	1.10	0.14	0.95	0.33	2.03**
Cancer Biology Research	0.57	2.47**	0.91	1.59	0.15	0.72	0.08	0.41	0.27	1.33
Control variables:										
Industry volatility	-0.11	-0.82	-0.29	-0.86	-0.04	-0.52	0.04	0.61	0.04	0.59
State innovativeness	0.03	0.57	0.25	1.70*	0.00	0.00	0.00	0.07	0.04	0.85
Firm age	0.22	2.76***	-0.12	-0.64	0.55	7.87***	0.56	9.09***	0.07	0.97
Year dummies	Incl.		Incl.		Incl.		Incl.		Incl.	
R^2	0.19		0.20		0.48		0.49		0.29	
Adjusted R^2	0.11				0.42		0.43		0.22	

N= 367; *** p<0.01; ** p<0.05; * p<0.1

[47] OLS model was used to estimate Equation 1, Logit model to estimate Equation 2, and SUR model to estimation Equations 3, 4 and 5.